ESSAYS ON CARBON ABATEMENT AND ELECTRICITY MARKETS

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In the first chapter of this dissertation, I study the effects of a number of policies which affect the electric grid using the SuperOPF, a full AC optimization/simulation framework with optimal investment developed at Cornell University. A 36-node model of the Northeast Power Coordinating Council is used to test policies that aim to reduce CO2, other emissions, or otherwise impact the operation of the electric grid: a base case, with no new environmental legislation; enactment of the Kerry-Lieberman CO2 allowance proposal in 2012; following Fukishima, a retirement of all US nuclear plants by 2022 with and without Kerry-Lieberman; marginal damages from SO2 and NOX emissions charged to coal, gas and oil-fired generation; plug-in hybrid electric vehicle load filling; wind incentives in place; and two cases which combine these. The cases suggest that alternative policies may have very different outcomes in terms of electricity prices, emissions, and health outcomes. In all cases, however, the optimal strategy for future investment is investment in new natural gas combined cycle plants. Policies can change how much new generation is built, whether other plants are built, or what types of plants are retired.

The second chapter of my dissertation utilizes the SuperOPF and the model of the Northeast Power Coordinating Council to analyze the issue of carbon leakage. I analyze the effects of a regionally-limited carbon cap and trade program, the Regional Greenhouse Initiative (RGGI), when additional generating assets in non-affected states

are included in the analysis. In the face of different carbon prices on generating assets in covered and non-covered states, generation is expected to shift from states bound by RGGI to states outside of RGGI. This carbon leakage may undermine some or all of the benefits of RGGI while simultaneously increasing prices for customers in the area. Even though carbon prices under RGGI are very low, some leakage is occurring, and this leakage will worsen if carbon prices increase. Ultimately, a unified policy offers greater carbon reduction at a lower cost, which would increase popular acceptance of such policies.

In the third chapter of this dissertation, my coauthors and I examine the issue of demand for carbon reductions. Recent large-scale field experiments have shown that peer information nudges can have significant effects on behavior, inducing people to reduce their production of negative externalities. Related work in psychology demonstrates that inducing feelings of personal culpability by showing people information about their peers can induce pro-social behavior. This study uses a contingent valuation experiment and a parallel lab experiment to further explore patterns of responses that have been suggested in the emerging literature on norm-based environmental interventions The field–level finding of asymmetric responses between those whose environmental or group impacts are above or below the norm is found to be robust across decision settings.However, substantial heterogeneity in responses to peer information is observed across a number of demographic and other respondent–specific dimensions not able to be explored in large scale field experiments, raising questions about the universality of peer-information effects and the design of such programs.

BIOGRAPHICAL SKETCH

John Timothy Taber has accepted a position as Economist with the Federal Energy Regulatory Commission, Office of Energy Policy and Innovation. John received his Ph.D. in the Dyson School of Applied Economics and Management at Cornell University in 2012. He holds and Bachelor of Science in Physics and a Bachelor of Arts in Economics from the Ohio State University in Columbus, Ohio and a Master of Science from the Dyson School of Applied Economics and Management at Cornell University. At Cornell University, John was awarded the Cyril F. Crowe Fellowship for Teaching and won the CALS Outstanding Graduate Teaching Award.

John is an energy and environmental economist with interests in behavioral and experimental economics. He uses models of the electric grid to explore the impacts of proposed and actual policies that impact the operation of the electric grid. Additionally, he uses contingent valuation and laboratory experiments to better understand mechanisms that impact peoples' willingness to pay for green electricity and other forms of carbon abatement. His current work is focused on expanding the scope and complexity of the model of the electric grid used in this dissertation from the northeastern United States to the Eastern Interconnect. John has presented his work at the Southern Economics Association, the Eastern Economics Association, the Western Economics Association, the Association for Public Policy and Management, and the United States Association for Energy Economics.

To Jamie

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PREFACE

CHAPTER 1

MAPPING ENERGY FUTURES: AN INTEGRATED ECONOMIC, ENGINEERING AND ENVIROMENTAL APPROACH TO ELECTRIC POWER

John Timothy Taber[1]

ABSTRACT

There are a number of national energy models used for investment planning and studying the effects of proposed environmental policies on the electric grid. No model to date has included data about actual generators, a network model for the electric grid, and emissions. In this study, the SuperOPF, a full AC optimization/simulation framework with optimal investment developed at Cornell University is used to study the effects of regulations on the Northeast power system. The Northeastern power system is represented by a simplified system of 36 nodes, which offers a compromise between computational tractability and accuracy, particularly in modeling the limits on important inter-system transmission lines.
In this paper, I study the effects of a number of policies that aim to reduce CO_2, other emissions, or otherwise impact the operation of the electric grid: a base case, with no new environmental legislation; enactment of the Kerry-Lieberman CO_2 allowance proposal in 2012; following Fukishima, a retirement of all US nuclear plants by 2022 with and without Kerry-Lieberman; marginal damages from SO_2 and NO_X emissions

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charged to coal, gas and oil-fired generation; plug-in hybrid electric vehicle load filling; wind incentives in place; and two cases which combine these. The cases suggest that alternative policies may have very different outcomes in terms of electricity prices, emissions, and health outcomes. In all cases, however, the optimal strategy for future investment is investment in new natural gas combined cycle plants. Policies can change how much new generation is built, whether other plants are built, or what types of plants are retired.

I. Introduction

The electric power industry in the United States will face a number of challenges in the coming years. To facilitate energy independence, energy usage may swap from the transportation sector to the electricity sector with the addition of plug-in hybrid electric vehicles. Increased electricity loads may also arise as other energy users try to find sources of energy that emit less CO_2. Restrictive caps on CO_2 emissions from generation, and the possibility of regulations on the emissions which cause fine particulates will affect the electric generating industry and the usage of the electric grid. Finally, an artificial cap on offer prices in electricity markets prevents a free market solution for optimal investment, which requires ancillary markets in reliability, capacity, and planning.

Several energy and electricity planning models exist, though none of them have both integrated environmental modeling and a model of the electric grid that incorporates enough real-world engineering constraints to accurately model power flows. For example, the ICF's Integrated Planning Model (EPA 2011) is used by the

EPA to estimate the effects of environmental policies on the electric grid, including the Cross-State Air Pollution Rule and the Transport Rule. However, while the IPM does have very detailed information about every generator in the United States including information about emissions for various pollutants, its transmission model lacks essential details. The IPM breaks the continental United States down into a few dozen regions for analysis. Within each region, transmission is unconstrained, and power flows between regions are constrained by aggregate flow limits. This model ignores the structure of the electric grid entirely, replacing it with a "bubbles and pipes" model for ease of analysis. The Resources for the Future Haiku model (Paul and Bertaw 2002) also uses constraints between regions to model flow limits, and uses "46 model plants" to estimate generation technology. The National Energy Modeling System (NEMS) supported by the Department of Energy has neither integrated modeling of air quality or a model of the electric grid (EIA 2009). These planning tools are useful, but may fail to capture the full impact of new policies because they ignore the realities of the electric grid, which constrain the ability to minimize costs and dispatch cleaner sources of energy.

The reduced network model of the electric grid described in this paper includes complete information about every generator in the Northeast Power Coordinating Council (NPCC) expected in 2006 to be online in 2008, as well as an equivalenced model of the underlying electric grid. It may be used to model policies that may change the cost of generation, demand for electricity, and generation mix. Nine cases are analyzed to show the possible uses of this model, which use one or more of the following changes to the electric grid: a proposed carbon cap-and-trade law, the elimination of nuclear power plants, incentives on renewable electricity, emissions taxes based on marginal damages, and the addition of electric vehicles to the electric grid.

The remainder of this paper is organized as follows. In the next section, I describe the optimization problem solved to optimize investment and generator dispatch. A description of the network model for the electric grid and information about generators is also provided. In the third section, I describe the policies modeled to produce the nine alternative cases. In the fourth section, I discuss the results of each of these cases and compare them. In the final section, I provide conclusions.

II. Model Description and Data

To simulate actual real electricity generation and capacity investment in a power market, the following optimization problem is solved:

$$\max_{p_{ijk},I_{ij},R_{ij}} \{\sum_i \sum_j [(\sum_k H_k(B_{jk} - (c_i^F + a_{jk}e_i)p_{ijk})) - (c_i^T(p_{ij}^0 + I_{ij} - R_{ij}) - c_i^I I_{ij})]\}$$

$$\text{subject to}$$

$$\begin{aligned} p_{ij}^0 + I_{ij} - R_{ij} &\geq p_{ijk} \\ p_{ijk} &\geq \alpha_i^{min}(p_{ij}^0 + I_{ij} - R_{ij}) \\ K_{ij} &\geq I_{ij} \\ \sum_j L_{jk} &= \sum_i \sum_j p_{ijk} \\ \textit{DC network constraints} \end{aligned}$$

i: generator index
j: node index
k: representative hour index
p_{ijk}: aggregate real power output from generator i at node j during representative hour k
p^0_{ij}: existing generator capacity
R_{ij}: capacity retirement
I_{ij}: capacity investment
c^F_i: cost of fuel, operations and maintenance per MWh
c^T_i: cost of taxes and insurance per MW
c^I_i: annualized cost of new investment
H_k: hours system is at load profile k
e_i: emissions vector for generation type I, tonnes/MWh
a_{jk}: emissions cost vector at node j in hour k, \$/tonne
α^{min}_i: min generation for type i
K_{ij}: max investment in fuel type I at node j
B_{jk}: Benefit function for demand response
L_{jk}: Net load

The objective function aims to maximize the net benefits of the value of generation minus the sum of power and fixed costs, subject to active power flow equations and transmission, generation, voltage and other constraints.[2] Since we are using a DC approximation of the actual AC electric grid, we can ignore costs and constraints involving reactive power and voltage angles. A DC approximation is a good model for these purposes (Schulze, 2009), and also ensures the problem is linear, which aids in computational tractability.

[2] This step of the analysis was performed using the SuperOPF and MATPOWER, a collection of MATLAB M-files for solving "stochastic, contingency-based, security-constrained optimal power flow[s]." The MATPOWER home page can be found at: http://www.pserc.cornell.edu/matpower. The SuperOPF is still under development. In terms of the terminology in the SuperOPF, the different representative hours are treated as contingencies from the base case (summer peak), and the Positive Active Reserve Price is the fixed cost or the investment cost, depending on if the generator is an existing unit or a new (potential) unit. Since we are representing an entire year with each contingency instead of the normal time frame of the SuperOPF, ramp rates are unimportant, and each generator has ramp rates equal to its maximum power output. However, to keep coal plants from cycling on and off between seasons, their minimum contracted power is set to 15% of PMAX.

Each year is split into sixteen representative hour types: four representative hour types for each season. Figure 1.1 shows the percentage of the year modeled by each representative hour. The summer representative hours make up a greater portion of the year relative to the other seasons because in this model, summer comprises more months than any other season: May through September. The fall and spring hours comprise two months each: October and November, and March and April, with the remaining three months falling into the winter category.

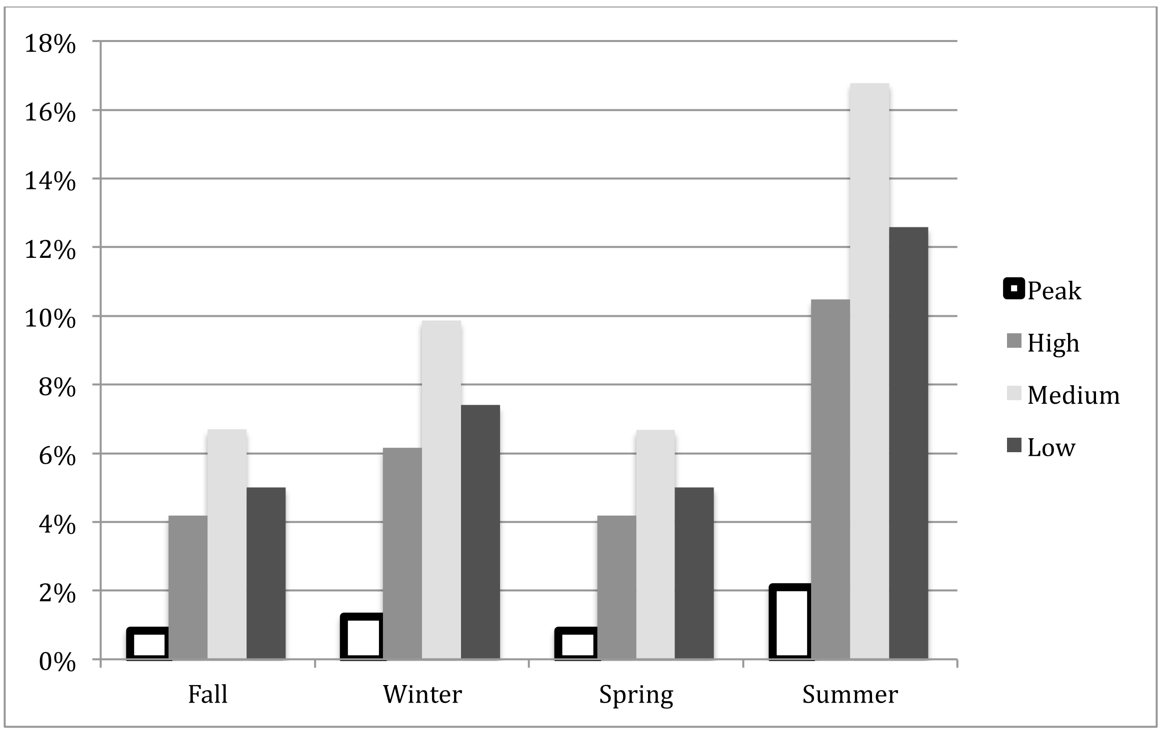


FIGURE 1.1: Relative Frequency of Representative Hour Types

Each representative hour is modeled as a deviation from the base hour, summer peak. Generators are de-rated in each season, which reduces their maximum power capacity, to simulates unit availability. Generator availability is highest during the peak seasons (summer and winter) because generators are required to carry out maintenance during the spring and fall, when demand is lower. Load can be scaled (separately for each area in the model) and different emissions costs can be applied. Figure 1.2 presents an average of the load scaling across all regions for each representative hour. The summer peak has the highest total system demand. Most regions experience their peak demand at the summer peak due to summer cooling needs. The Maritimes in Canada, however, actually has its annual peak during the winter. Investment in units, especially new units needed to meet this peak demand (often called peaking units), is driven by this representative hour. Although the summer peak represents only a small portion of total hours, there must be enough capacity on hand to provide for this demand, since storage on a utility scale is prohibitively expensive with current technology. In the real world, there exist peaking units that are only used for a few hours for a few days each year, usually on hot afternoons in July and August. These units are typically older oil or natural gas units that have very low fixed costs but very high operating costs.

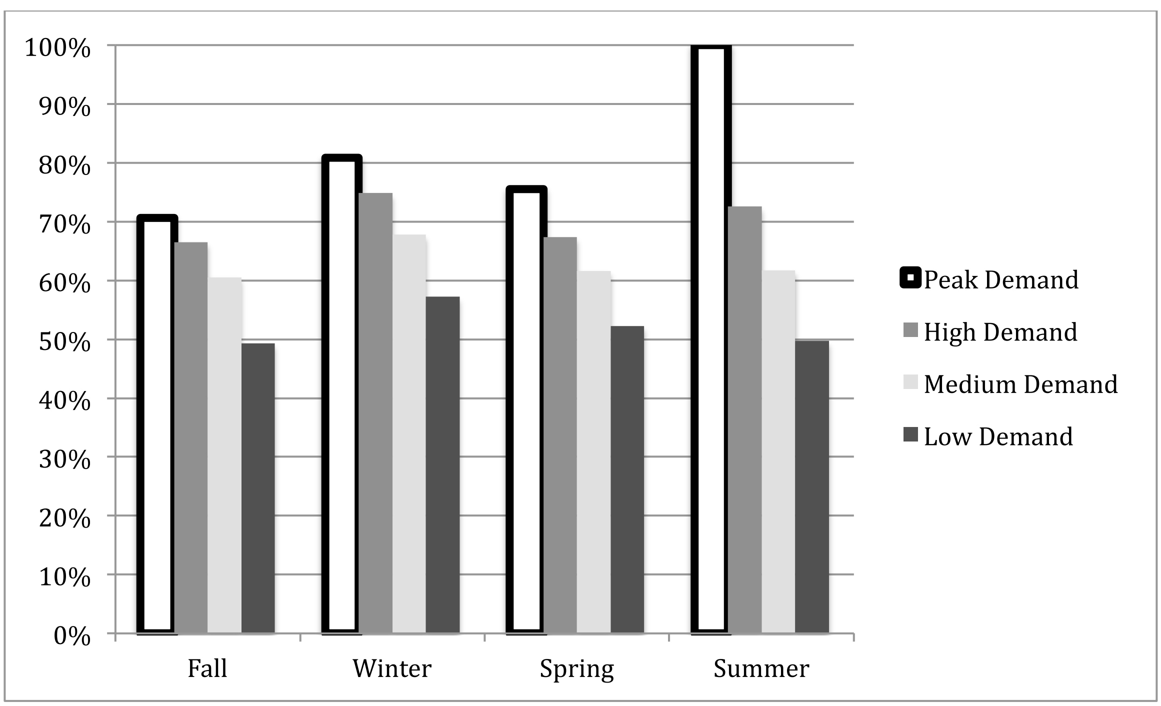


FIGURE 1.2: Average Demand Assumptions for Representative Hour Types

Accurate modeling of costs arising from emission policies is central to the accuracy of this paper. Many emissions laws in the United States propose cap-and-trade programs, which operate by putting a cap on the total amount of emissions, distributing emissions allowances, usually by endowment or auction, and establishing a permit market with a price for these permits. A firm that expects to exceed its emissions allotment based on the number of allowances it owns may reduce emissions or purchase additional permits. Firms are expected to minimize the costs of these two options to maximize their profits. A cap-and-trade program, like an emissions tax (which places a tax on each unit of emissions), puts a price on each unit of emissions. Examining the response of the power industry to a price on emissions allows us to predict the effect of a cap-and-trade program as well as an emission tax program. The term "emissions price" is used to refer to either the permit price in a cap-and-trade program or the emission tax rate. Firms that are endowed with permits should still value their opportunity cost even if they represent windfall earnings.

Information about fixed and investment costs for generation plants, as well as information about operating costs for new plants was obtained from the Energy Information Administration (2011). Four types of new plants were selected to be built: dual unit advanced pulverized coal, advanced natural gas combined cycle, dual unit nuclear, and onshore wind. These four plants represent efficient versions of four of the most common types of electric power used in the United States for which investment is possible. The overnight cost reported by the EIA was converted into a total cost by assuming an equal portion of the overnight cost was spent at the beginning of each year, and the debt accrued interest at an annual rate of 8%. A power plant can be expected to pay back its investment in the first 10 years of operation, so a capital recovery factor was calculated using equation (4). Summary information about existing generators is provided in Table 1.1. Although costs are treated as linear in this simulation, real-world costs are non-linear. Most plants have greater thermal efficiencies when running at higher outputs, and thus lower marginal cost. Natural gas combined cycle plants in particular have much lower efficiencies and thus much higher costs if their second stage steam turbines cannot be used. However, most of the plants in the sample, and many plants in the real world, both peaking and baseload units, are either off or at full generation. The exception is mainly coal plants, which are generally hard to start from cold and may cycle from low output to high output over the course of a day or a season. In the aggregate, the linear cost assumption should not affect the results of the simulation greatly, and it also an assumption shared by many planning models developed for the power industry.

TABLE 1.1: Information about Existing Generators

Fuel Type	Fixed Cost $/MW	Total Variable Cost $/MWh		
		Mean	Min	Max
Coal	$29,670	$37.26	$22.14	$293.16
Natural Gas	$14,620	$72.32	$39.47	$240.11
Wind	$28,070	$0	$0	$0
Nuclear	$88,750	$2.04	$2.04	$2.04
Oil	$14,620	$283.84	$31.47	$1,040
Hydro	$13,440	$0	$0	$0
MSW (Municipal Solid Waste)	$373,760	$0	$0	$0

$$CRF = \frac{i(1+i)^n}{(1+i)^n - 1} \qquad (4)$$

CRF: Capital Recovery Factor
i: Interest Rate (8%)
n: Compounding Periods (10 Years)

For ten years and an annual interest rate of 8%, a plant is built if it can cover 14.9% of the total construction cost in the first year of operation. Generation costs assume prevailing rates for fuels are the same as the average in the region for 2010: $5.56/thousand cubic feet for NG and $2.82/MBTU for coal. In line with DOE estimates, natural gas prices increase by about 20% in 2022, and a further 23% in 2032. Coal prices decrease slightly (98% of 2012 costs) in 2022, and increase 4% from that value by 2032. Total capacity additions are limited to 15% of the maximum rate in a 5-year period in which each type of fuel has, historically, been built in the entire United States. This corresponds to the NPCC's share of total US electrical generation. For example, between 1985 and 1990, approximately 34 GW of nuclear capacity was built in the United States. Thus, 5 GW is a conservative upper limit for the nuclear capacity that could be built by 2022 in the NPCC. Information about new generators is summarized in Table 1.2.

TABLE 1.2: Information about New Generators

Fuel Type	Capital Recovery/Year $/MW	Total Variable Cost $/MWh	Total Possible Capacity Additions
Coal	$497,201	$29.05	10 GW
Natural Gas	$181,824	$39.05	32 GW
Wind*	$392,322	$0	3.5 GW
Nuclear	$1,141,454	$2.04	5 GW

*Wind assumes an average capacity factor of 33%, excluding federal and state incentives.

The distribution of demand and the tradeoff between fixed and variable cost drives the investment and maintenance of different kinds of units. For example, roughly 30% of the year has an expected load at about half of peak load: The low demand case for each season in Figures 1.1 and 1.2. (And the entire year has a demand at half of peak load or more.) For a power plant running 8,760 hours a year, total costs for an average fossil-fuel plant range from a low of $356,000/MW for a coal plant to over $2.5 million dollars/MW for an oil plant. However, if a plant is only running for the summer peak, 184 hours a year, the average natural gas plant costs under $28,000/MW to operate, cheaper than any other plant type except for hydropower.

This analysis uses a network reduction of the Northeastern United States developed by Allen, Lang and Ilic (2008.) A diagram of this network is shown in Figure 1.3. Each point on this diagram represents a bus in the network, which are both numbered and named by the independent system operator or planning authority. The spatial layout of the busses roughly corresponds to their geographic location. The two lone busses at the top of the figure are Hydro Quebec and New Brunswick. The five busses at the left side correspond to Ontario, which connect into the western New

York System. The entire middle of the diagram and the bottom right correspond to busses in New York, which connect to Pennsylvania and New Jersey (at the bottom left) and New England (at the middle right.) The lines connecting these busses correspond to the actual or equivalenced lines in the real world. In this work, Allen et al. reduced the Northeast Power Coordinating Council area to a 36 bus[3] model, while maintaining important line flow constraints. Having an accurate model of the network over which electricity flows is vital. Consider the highly simplified power network depicted in Figure 1.4. In this network, power can flow from the generator on the left to the load on the right via two pathways. If each segment has equal resistance and length, Kirchoff's Law will predict that 1/3 of the electric flow will along the upper path, and 2/3 will flow along the bottom path. In an actual electric grid, power flows from generator to load along all possible pathways simultaneously, which means changes in generation or load at one node can cause transmission congestion at nodes far removed. Conversely, transmission limits at lines far removed from the shortest path between a generator and a load may reduce the total power able to flow from a source to a load. Lines which carry more power than their rated capacity for too long actually warm up and sag, which may cause them to dip into trees and ground out. One of the causes of the Northeast Blackout of 2003 were power lines in Ohio sagging into trees, which triggered a chain reaction and ultimately destabilized the electric grid.

[3] A bus is one node on the network, usually containing both load (customers) and generating units and connected to other busses via transmission lines.

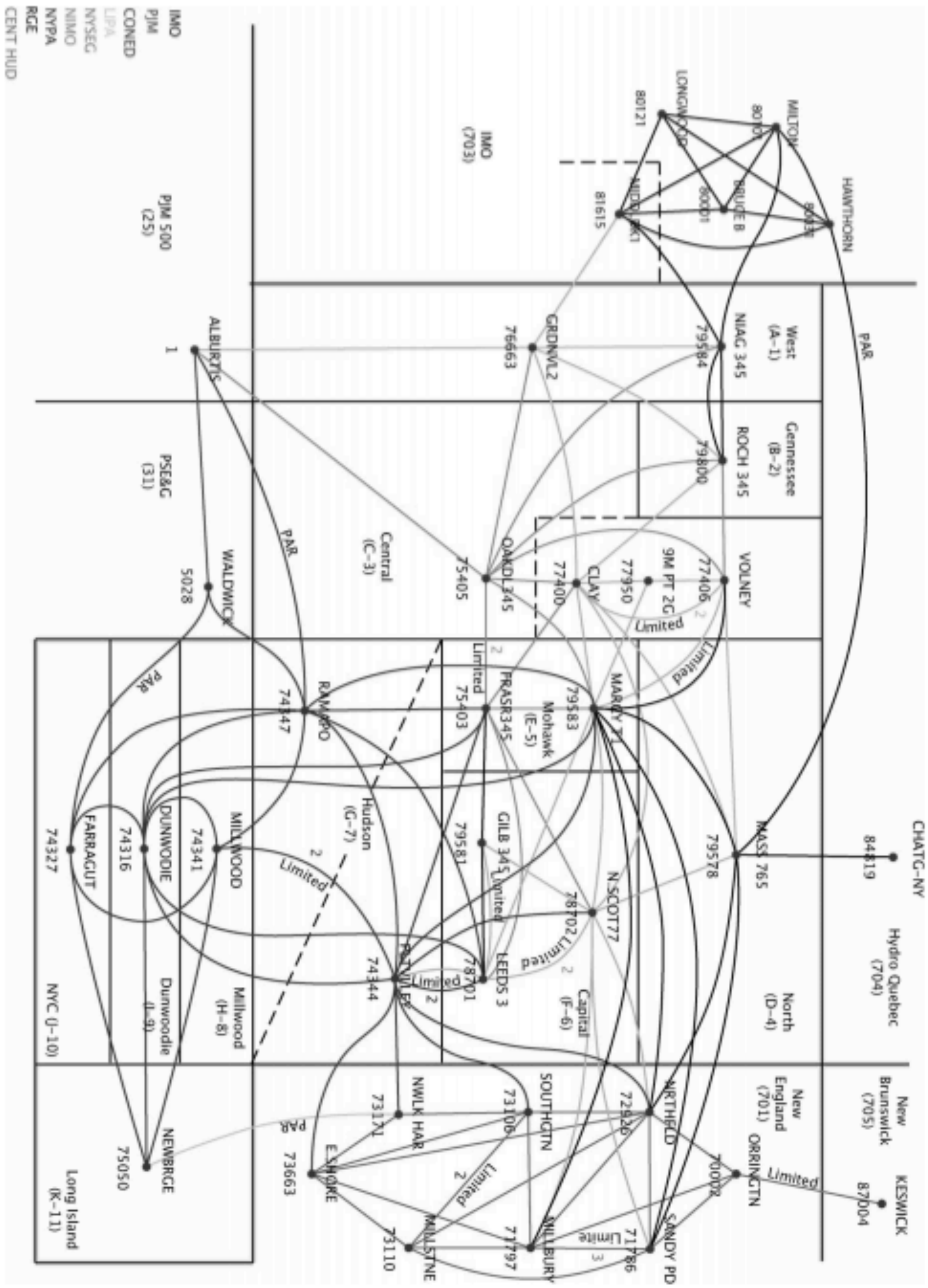


FIGURE 1.3. Diagram of 36-bus model from Allen et al. (2008).

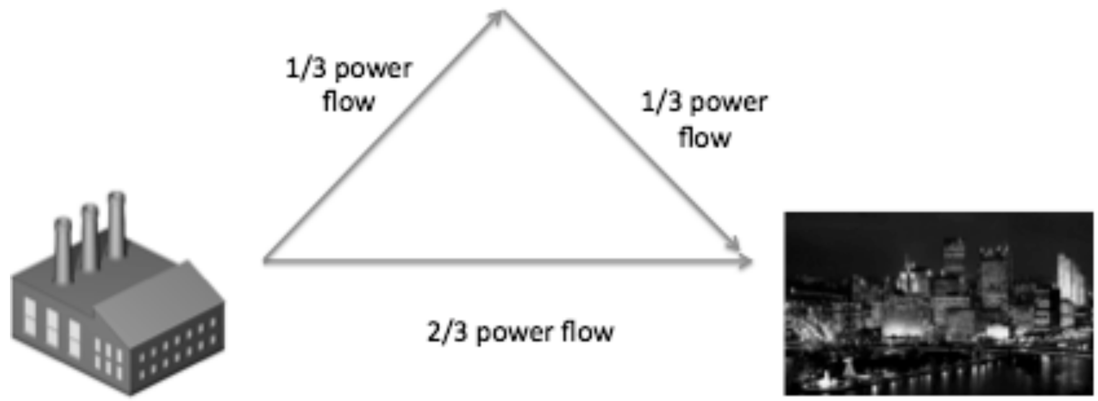


FIGURE 1.4. Schematic of Electricity Network

Data on existing generating units, provided by Energy Visuals, came from the 2006 reliability planning process of the Multiregional Modeling Working Group, and includes data on units projected to be operational in the summer of 2008. Data on fuel type, heat rate, generation cost, and emissions of CO_2, SO_2 and NO_X are included for each plant. For more details on this stage of the analysis, refer to Schulze et al (2009.)

The benefits function for demand response is based off the long-run elasticity and growth rates for elasticity. As electricity prices increase, whether due to natural growth of the system, or to added costs to generation from emissions prices, people will respond by cutting back their level of power consumption. In the long run, the elasticity of demand for electricity is approximately -1 (Dahl, 1993). However, recent research suggests that, even in the short run, the elasticity of people responding to average prices (ie, utility bills) is -0.982 (Fell et all, 2011). Since each step of our model represents 10 years, an elasticity of -1 is used to represent demand response. Average distribution costs are assumed to be \$70/MWh. In the NPCC, the average

LMP (locational marginal price[4]) for the base year is also $70/MWh. Thus, $140/MWh is a good estimate for retail prices with no new policies. A 2.5% reduction in demand would be expected as prices increased to $143.50, or an increase in LMP from $70 to $73.50. Because this optimization problem must remain a linear program, demand response is represented in ten blocks, each representing 2.5% of total load. The effective price for each block of demand response is at the midpoint of each interval. Load is also expected to naturally grow as a result of increasing population and demand for energy. The New York Independent System Operator (NYISO) estimates this load growth at 0.59% per year (NYISO 2009.)

III. Description of the Nine Cases

Each of these cases was simulated for an initial year without investment: 2022. Each cycle of investment is assumed to take ten years. Ten years is enough time for any kind of power plant, including a nuclear plant to be built, assuming regulatory and siting issues could be resolved. The first cycle of investment thus ends in 2022, and the second investment cycle ends in 2032. For comparison, the first case modeled includes no environmental regulations or subsidies for power generation or capacity. This case is referred to either as the base case or the no regulation case.

The second case modeled is the American Power Act, often referred to as the Kerry-Lieberman CO_2 Cap and Trade Bill. The Kerry-Lieberman Bill proposed cap and trade auctions for CO_2 beginning in 2012, with a cap starting at the 2005 level, and a targeted reduction of 17% by 2020 and 42% by 2030. However, the bill also

[4] Because of transmission constraints, prices may differ from node to node. Most independent system operators have locational marginal prices, so the nodal prices are refereed to as LMPs.

included a price collar for CO_2 prices. The price floor would start at $12/ton, and increase by 3% annually in real terms, while the price ceiling would start at $25 and increase by 5% annually in real terms. Previous work (Schulze et al 2009) has shown that, with no new investment allowed, the targeted CO_2 reductions are unmet, and the CO_2 prices reach the ceiling by 2016. The addition of new investment might change this however.

In the third case, power plants are charged marginal damages equal to the health impacts of their SO_2 and NO_X emissions. The same air transport model from The Hidden Cost of Energy (2010) was used to calculate ambient SO_2, NO_X and fine particulate matter concentrations in every county in the NPCC as a result of emissions from every generator in the model. Finally, information about risks of morbidity and mortality from these emissions were used to calculate marginal damages for each plant. Table 1.3 shows summary information about these marginal damages and emissions. AES Cayuga[5], also known as Milliken Station, is a coal-fired power plant located on Cayuga Lake near Cornell University. It is an exceptionally efficient coal plant, mostly due to the fact that Cayuga Lake is a deep lake with an abundant supply of cold water, which makes for a very efficient thermal cycle. The maximum marginal damage coal plants are Portland Units H&L in Northhampton, PA, located less than 100 miles west of New York City. The average coal plant is 45 times more damaging than the average natural gas plant, and the most damaging coal plants cause

[5] AES Cayuga is chosen at a basis for comparison for several reasons. First, it is a very efficient coal unit with low emissions, so illustrates the lower end of emissions and damages. Second, it is near Ithaca, NY, so many power engineers and energy economists visiting the area have knowledge of the plant. Lastly, information about the plant is easy to verify, since many people at Cornell have experience with AES Cayuga.

twice as much damage as that. On the other hand, some coal plants, like AES Cayuga, are not very damaging. Nor are coal plants that lack significant population centers downwind, such as a coal plants on the Atlantic coast. Of course, the newest natural gas combined cycle plants are even more efficient than the average natural gas plants plant in this sample, and have correspondingly lower marginal damages in per MWh terms.

TABLE 1.3: Emissions and Marginal Damages for example generating units

Unit Name or Type	CO_2 Rate Tonnes/MWh	SO_2 Rate Tonnes/MWh	NO_X Rate Tonnes/MWh	Marginal Damages $/MWh
AES Cayuga 1	0.98	<0.001	<0.001	7.22
Average Coal	1.05	0.007	0.001	89.87
Max MD Coal	1.00	0.013	0.001	232.20
Average NG	0.65	<.0001	<0.001	2.36

In the fourth case, electrifying the transportation sector was investigated. Using a report from Berkeley (Becker et al 2009), an estimate for the total number of electric vehicles in 2022 and 2032 was used to increase the low demand hours on the grid, assuming that vehicles were charging at night. In 2022, 703 MW would be added to the low demand hours at each node, as a result of almost 600,000 plug-in hybrid vehicles with a 2kWh battery, and over 200,000 electric vehicles with 16 kWh batteries. By 2032, the Northeast might have 5,412 MW of additional demand (over 2012) from over 725,000 plug-in hybrid vehicles and around two million electric vehicles. This assumes that adoption rates for plug-in hybrids and electric vehicles are equally spread across the country, though some estimates suggest that western states would experience faster adoption rates than the northeast.

In the fifth case, incentives for wind generation are added. Policies modeled include the United States production credit for wind generation, and similar credits in Ontario, Quebec and the Maritimes. Some states offer subsidies to reduce construction costs, such as Massachusetts and Delaware. Because many states are aggregated into some buses in this model, an average value for every state in a region was used to model these policies. (For example, Bus 1 includes generation from Pennsylvania, Delaware, Massachusetts, Maryland and New Jersey.) Wind incentives currently in force are expected to continue through 2032.

After the earthquakes, tsunamis and Fukushima disaster in Japan, there was talk in New York about shutting down nuclear power plants, particularly those close to large populated areas, such as Indian Point Energy Center. Expanding on this idea, the sixth policy modeled decommissions all nuclear power plants in the NPCC by 2022, with no other regulations. The system lacks enough spare generating capacity to decommission the plants without building new generators. In a separate case, decommissioning nuclear power plants was combined with the proposed Kerry-Lieberman cap and trade bill as well.

Two additional cases were also modeled which combine several aspects of the previous cases in order to predict the most likely path of the power system to 2032 given current policies and expected developments, the best guess case, and the socially optimal path of the power system through 2032. For the best guess case, wind incentives are expected to stay in place through 2032, PHEV load-filling is expected to occur, and some form of CO_2 emissions control is expected to be in place starting in 2022, modeled by having CO_2 prices at the Kerry-Lieberman CO2 price cap and applied to all units greater than 25 megawatts. Estimated prices for the EPA's new Cross-State Air Pollution Rule are included, although a full modeling of the rules will not be accurate until the entire Eastern Interconnect and all of the covered states is included (EPA, 2011.) For the purposes of this simulation, generators in New York, Pennsylvania, New Jersey, Maryland, Delaware and Washington, DC are counted as Group 1 states. Although in the current proposed rule, Delaware and DC are exempted, there are only a few generators included, so it should not significantly impact the model. Group 1 states are charged \$1,000/ton of SO_2 emissions in 2012, and \$1,100/ton in 2022 and 2032. Annual NO_X emissions permits are expected to cost \$500 in 2012 and \$600 in 2022 and 2032, with permits during the summer ozone season (which corresponds to the summer representative hours in the model) priced at \$1,300/ton in 2012 and \$1,500/ton in 2022 and 2032. These emissions price are only charged on units greater than 25MW, as with most EPA emissions prices. As with generation costs, I assume that emissions are linear with plant output. Although this assumption is not strictly true (plants become more efficient as they increase their output) this assumption is close enough for the purposes of this analysis.

In the socially optimal case, marginal damages on SO_2 and NO_X emissions, PHEV load-filling and a \$30/tonne price on CO_2 are applied starting in 2022. \$30/tonne is the value for the social cost of carbon used in the Hidden Cost of Energy. Note that as in the Marginal Damages case, these costs are applied to all units, regardless of size (unlike the Kerry-Lieberman CO_2 prices, which are only applied to units larger than 25MW.)

IV. Results of the Nine Cases

Every case modeled has four figures. The first two figures show the actual levels of capacity and investment in the case, and the third and fourth figures show the changes in capacity (the left figure in each pair) and generation (the right figure) that occur from 2012-2022 and from 2022-2032. The maximum vertical scales on the first and second figures are the same for each case, to assist in comparing outcomes: 100 GW for the capacity figure, and 400 TWh for the generation figure.

The results for the no regulations case, also called the base case, are depicted in figures 1.5-1.8. For reasons having to do solely with the relative costs of the units, the optimal investment path for the system is to build new natural gas units and retire oil units. Oil units, especially in the Northeast, are mostly older units used as "peakers" to meet demand during peak load hours. They have some of the highest marginal costs, and it is not surprising that these units would be retired first. Approximately 12 GW of natural gas capacity is built by 2022, and a further 3 GW by 2032. The decline in natural gas generation between 2022 and 2032 is a result of older natural gas units being used less: their generation is 125 TWh is 2012, 69 TWh in 2022, and 46 TWh in 2032, while the generation of new natural gas units increases from 0 in 2012 to 92 TWh in 2032. Natural gas generation is essentially made up of two kinds of units: older natural gas generators, which are cheap to build but expensive to operation, and newer combined cycle turbines, which are a little more expensive to build (though still cheaper than any other generator) but cheap to operate.

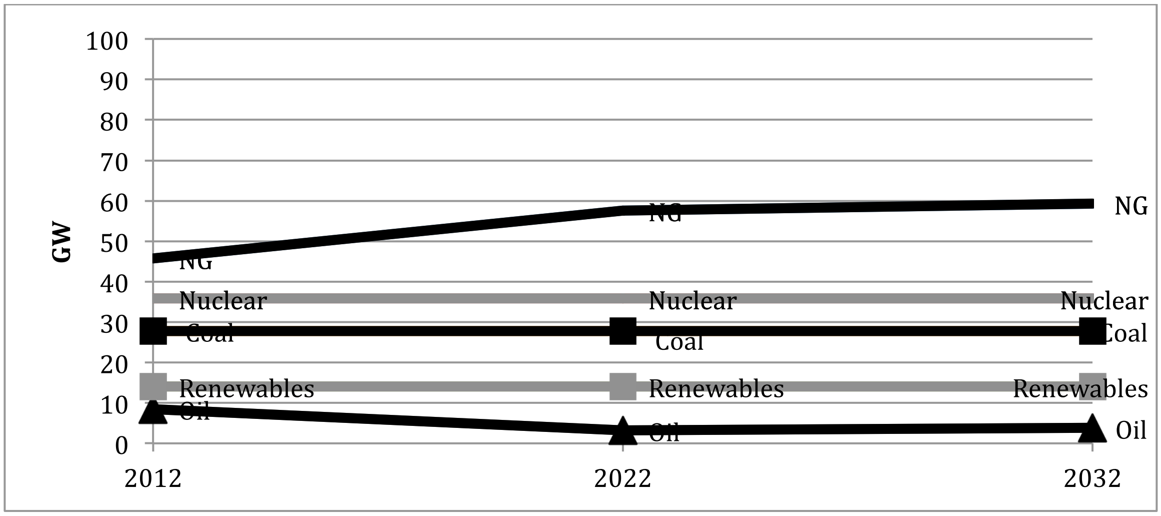


FIGURE 1.5: Capacity in the Base Case

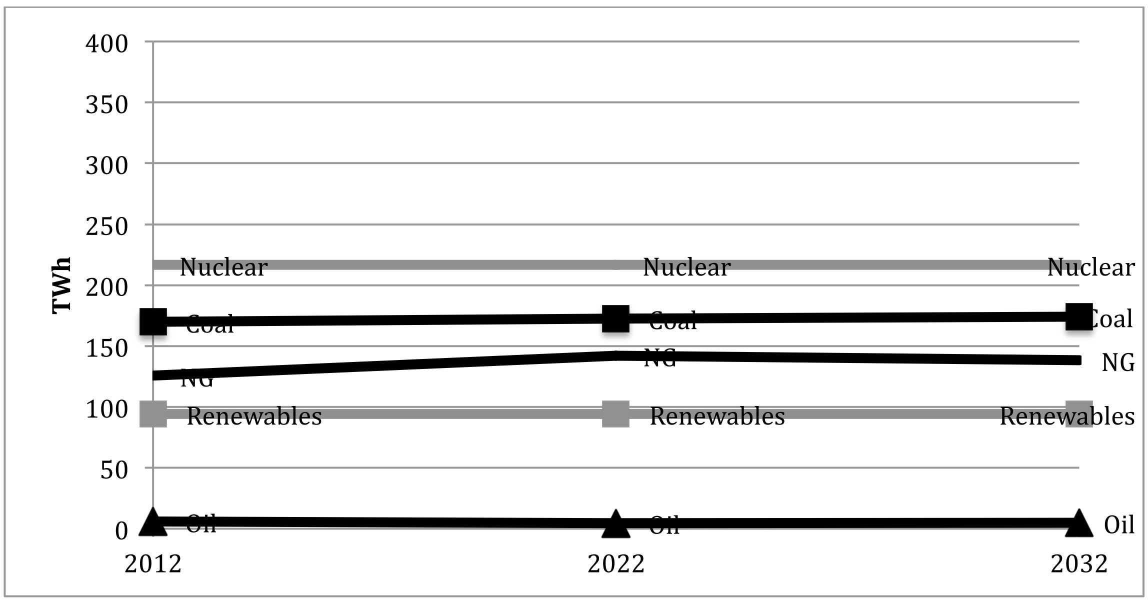
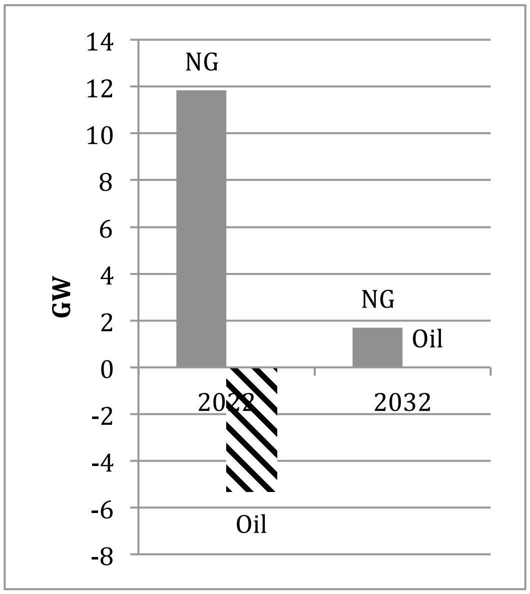
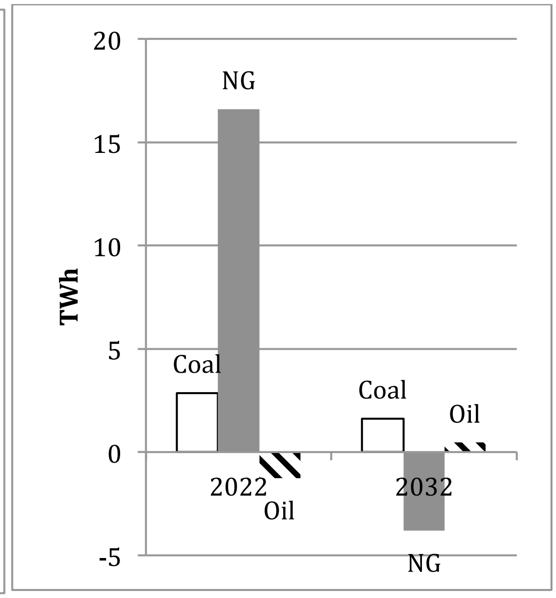


FIGURE 1.6: Generation in the Base Case





FIGURES 1.7 and 1.8: Capacity and Generation Changes in the Base Case

Figures 1.9-1.12 show the results of the Kerry-Lieberman CO_2 case. Imposing CO_2 prices reduces the capacity and generation of coal and oil units while increasing the capacity of generation of natural gas units, though these increases are less than they were in the base case. 12 GW of natural gas generation is added by 2022, though as in the base case, some old natural gas capacity is simultaneously retired. In 2032, these retirements outweigh the (modest) capacity additions. The Kerry-Lieberman CO_2 case has less total capacity and generation because higher prices than the base case lead to more demand response and less total load. Load in 2032 is at 89% of 2012 levels, despite a 12% growth in the pre-demand response base level of load.

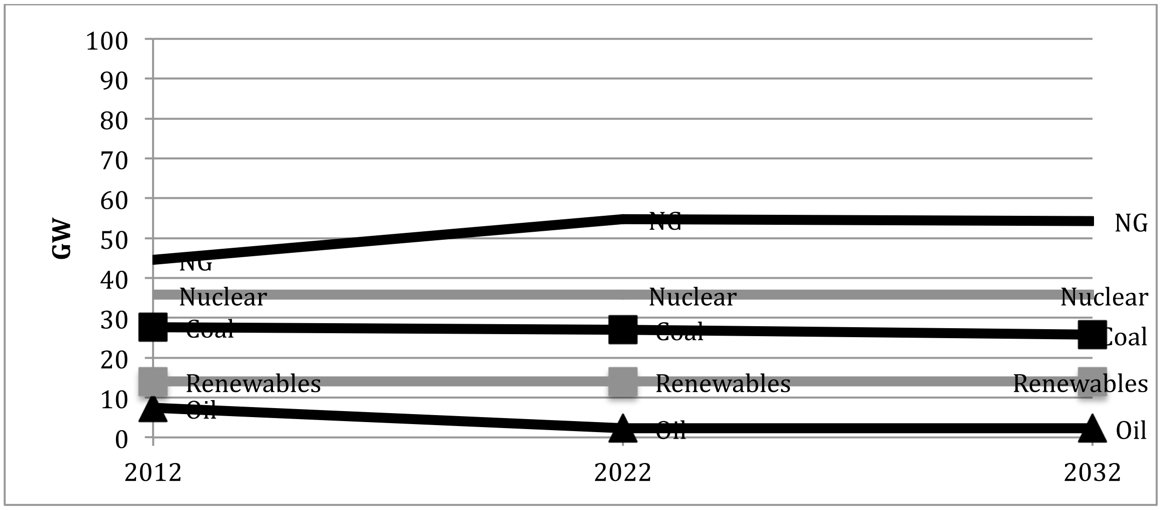


FIGURE 1.9: Capacity in the Kerry-Lieberman CO_2 Case

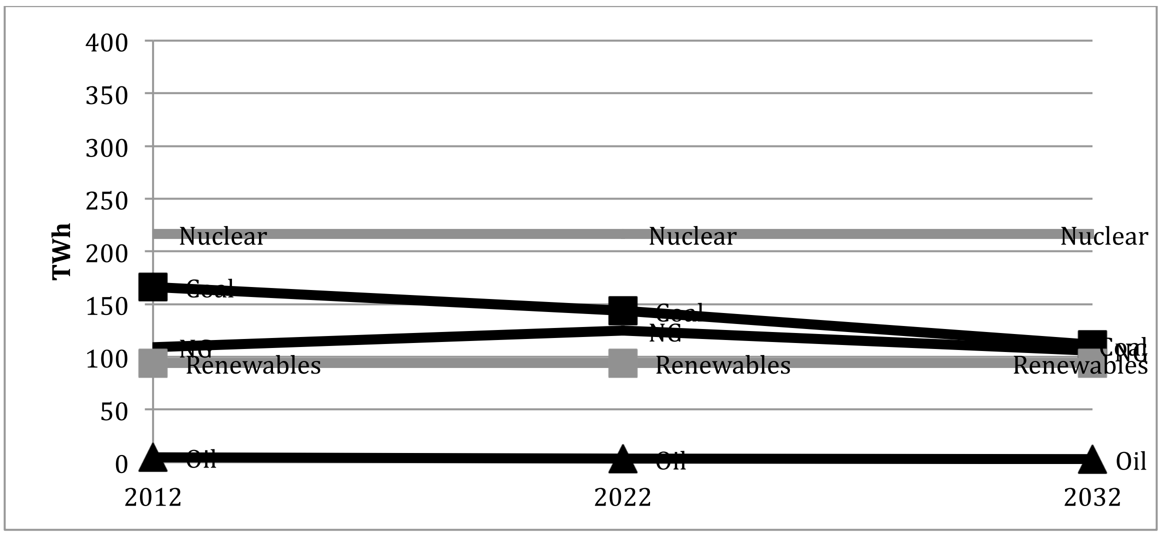
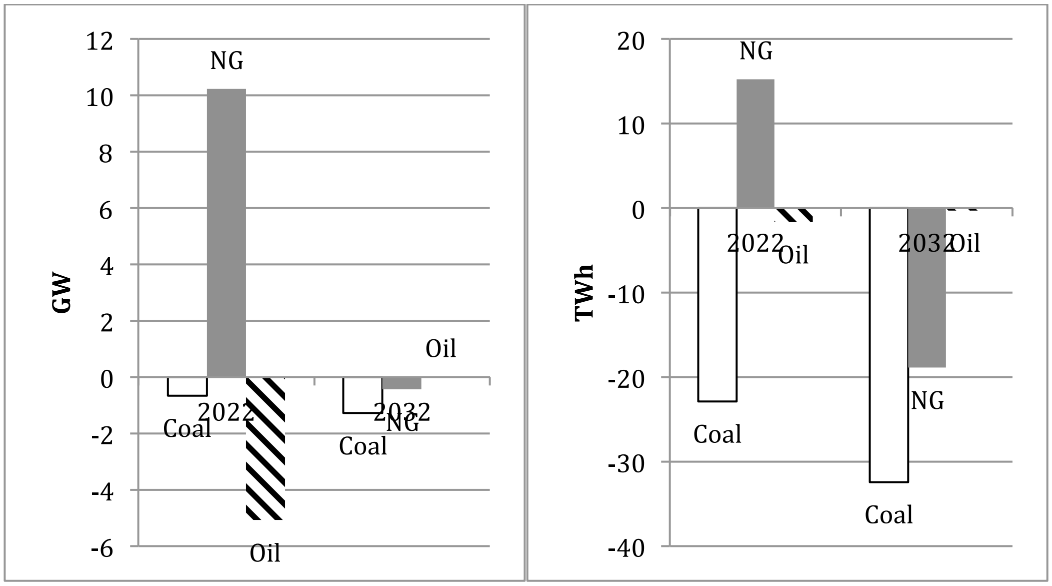


FIGURE 1.10: Generation in the Kerry-Lieberman CO_2 Case



FIGURES 1.11 and 1.12: Capacity and Generation Changes in the Kerry-Lieberman CO_2 Case

Figures 1.13-1.16 depict the results of the marginal damages case. Note that marginal damages are not applied until 2022, so the 2012 results are the same as for the base case. This case is very effective at forcing coal plants to retire. Almost 80% of coal capacity is retired by 2022, and the system builds natural gas plants and retires less oil plants to make up the difference. Combined with the availability of more efficient natural gas combined cycle plants, natural gas capacity increases by over 50% by 2022, and natural gas generation more than doubles. Price increases keep load growth to minimal levels, which explain the modest investment in new natural gas plants between 2022 and 2032.

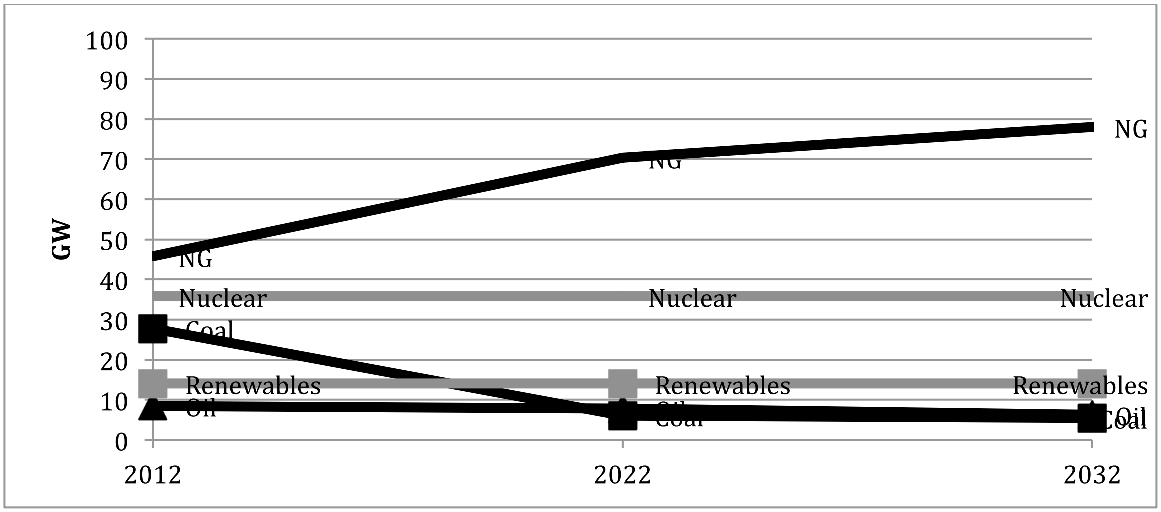


FIGURE 1.13: Capacity in the Marginal Damages Case

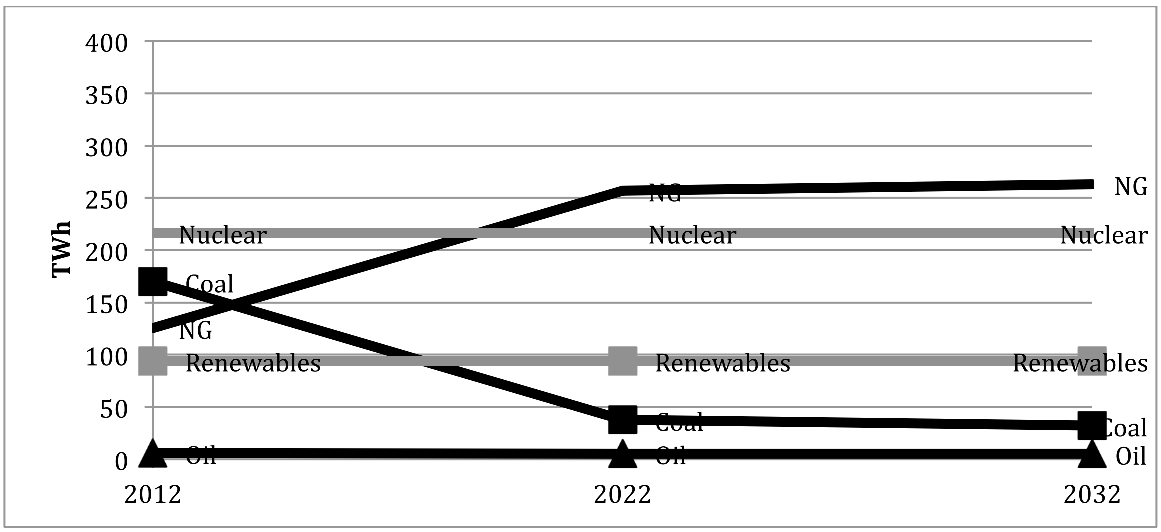
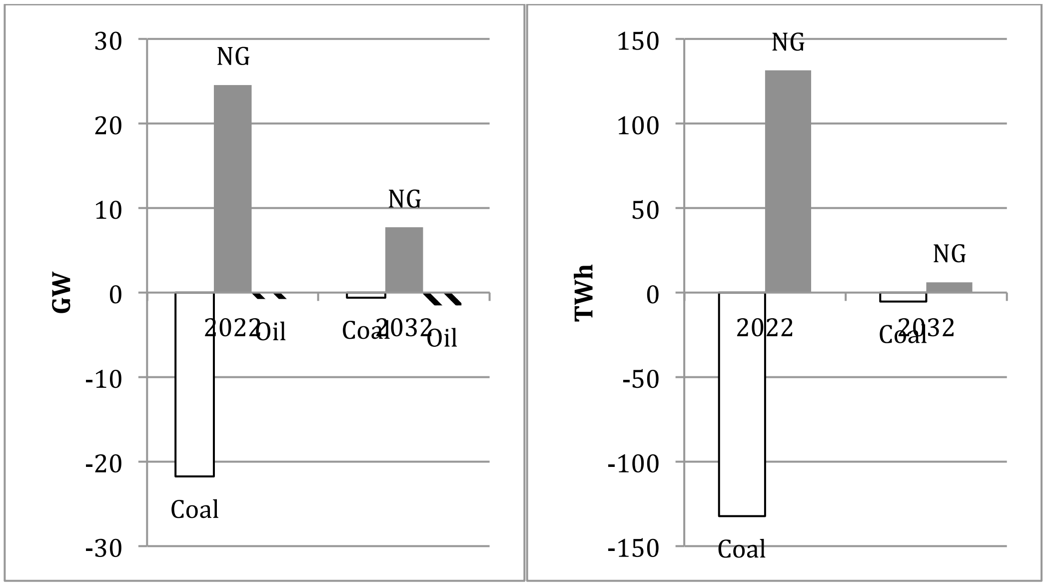


FIGURE 1.14: Generation in the Marginal Damages Case



FIGURES 1.15 and 1.16: Capacity and Generation Changes in the Marginal Damages Case

Figures 1.17-1.20 shows the results of the Plug-in Hybrid Electric Vehicles (PHEV) case. The results from the PHEV case are almost identical to the base case, except that slightly more natural gas capacity is built, and slightly more oil capacity is decommissioned. There are similar changes in generation as well. Raising the low demand hour increases the need for base load generation, which is met by new natural gas combined cycle units, and reduces the need for oil peaking. Generation from natural gas units increases from 2022-2032, the most obvious departure from the base case.

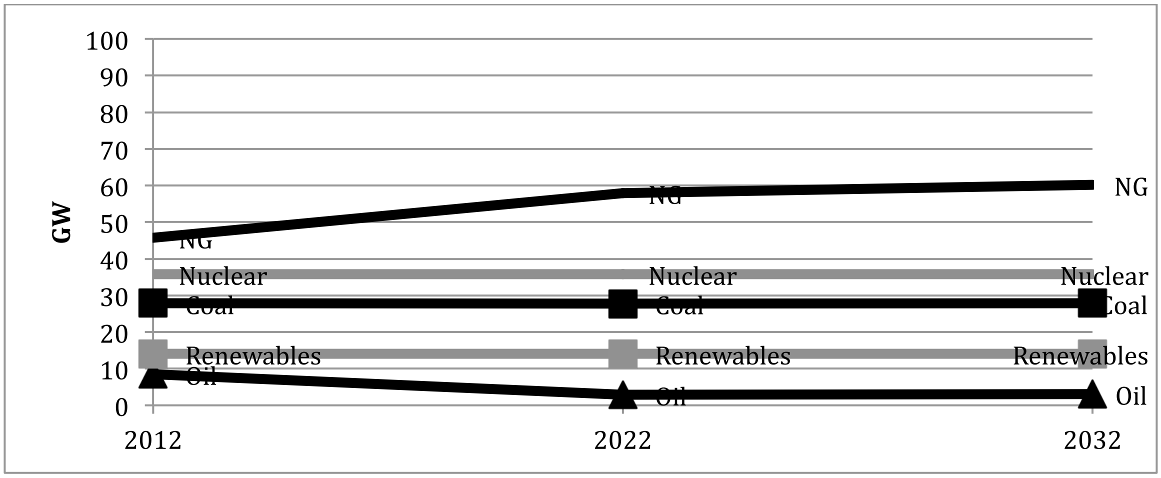


FIGURE 1.17: Capacity in the PHEV Case

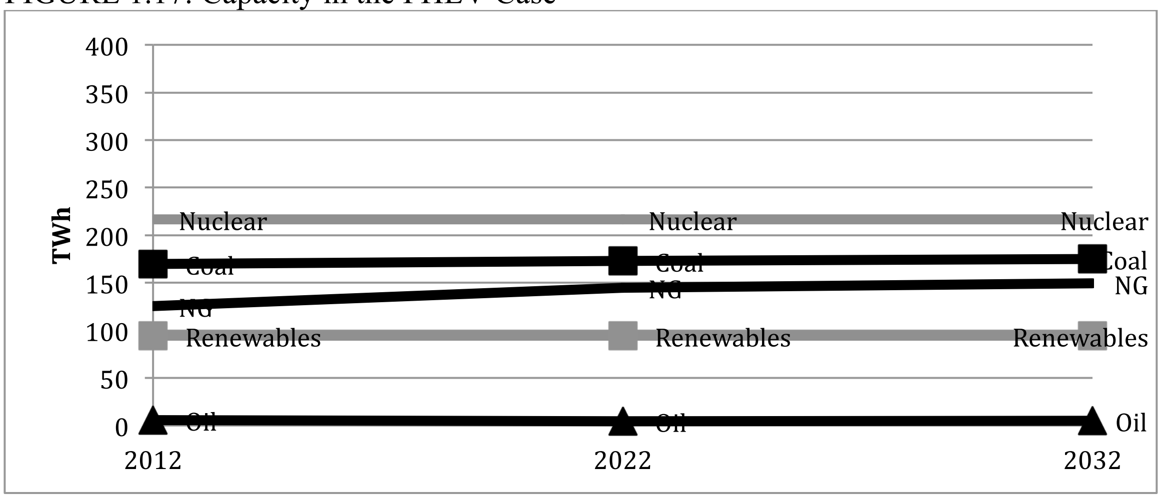


FIGURE 1.18: Generation in the PHEV Case

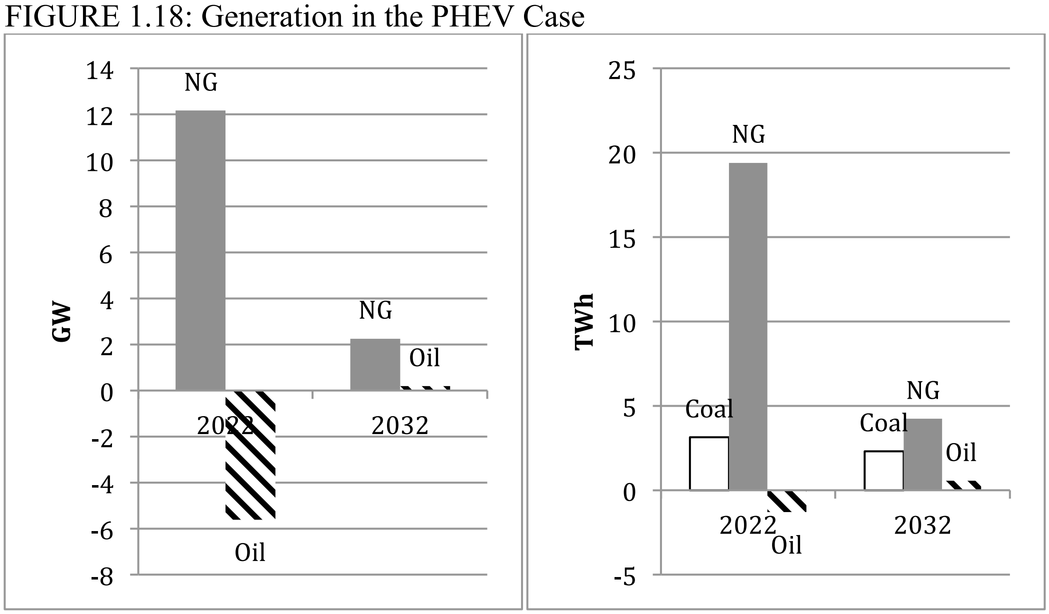


FIGURE 1.19 and 1.20: Capacity and Generation Changes in the PHEV Case

Figures 1.21-1.24 show the results for the wind incentives case. For the first time, something other than natural gas capacity is built: wind turbines. These wind generators are built at the expense of natural gas capacity, though almost 15 GW of new natural gas capacity is built by 2032, just a just a little less than the base case. The subsidies on wind generation actually lower the average wholesale price of electricity and lead to smaller decreases in load, so total generation is somewhat higher than in the base case. The decrease in natural gas capacity between 2022 and 2032 is, like the Kerry-Lieberman case, driven by the retirement of old natural gas generators, not newer combined-cycle turbine units.

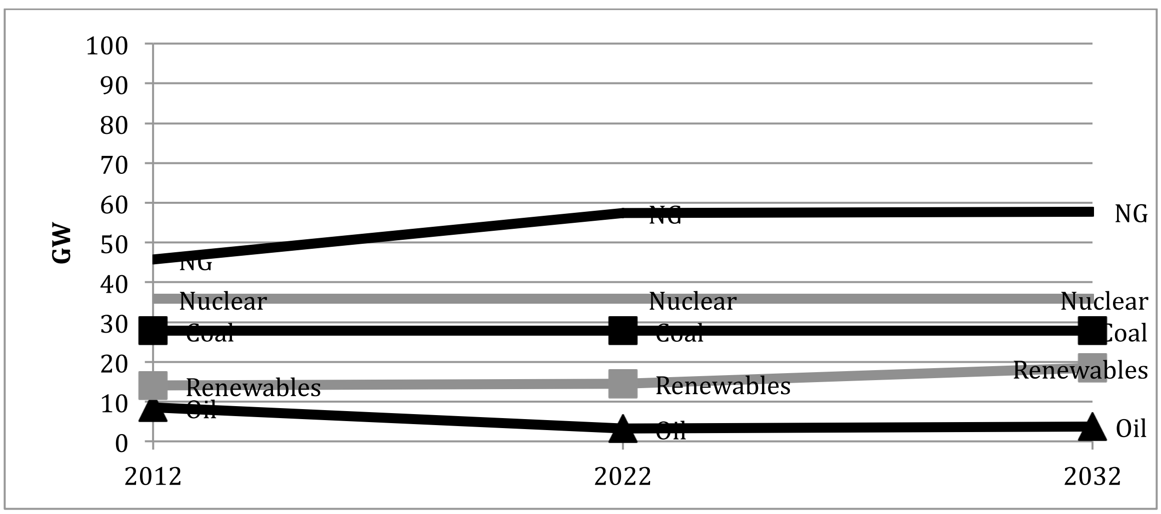


FIGURE 1.21: Capacity in the Wind Incentives Case

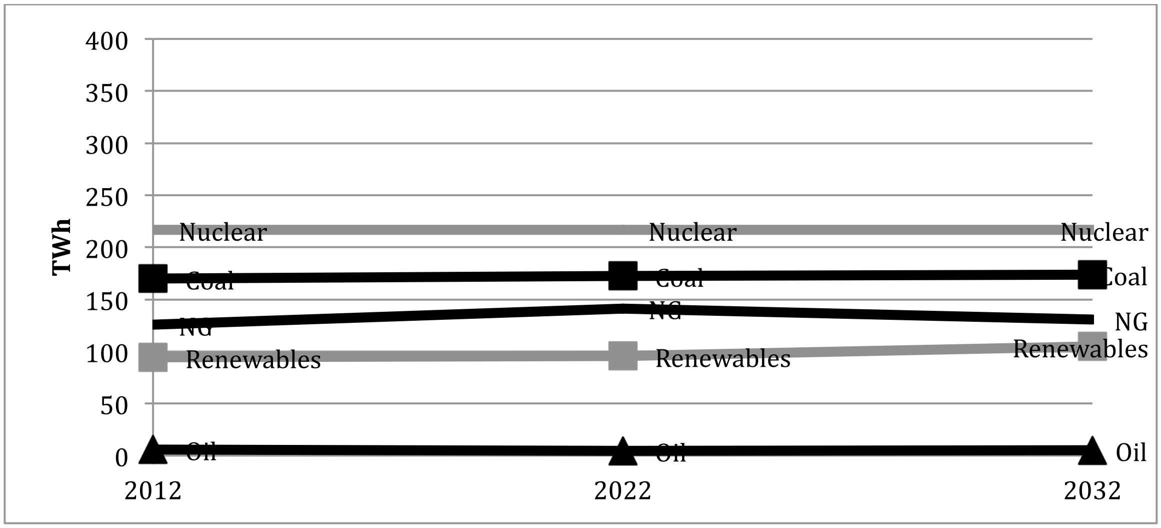
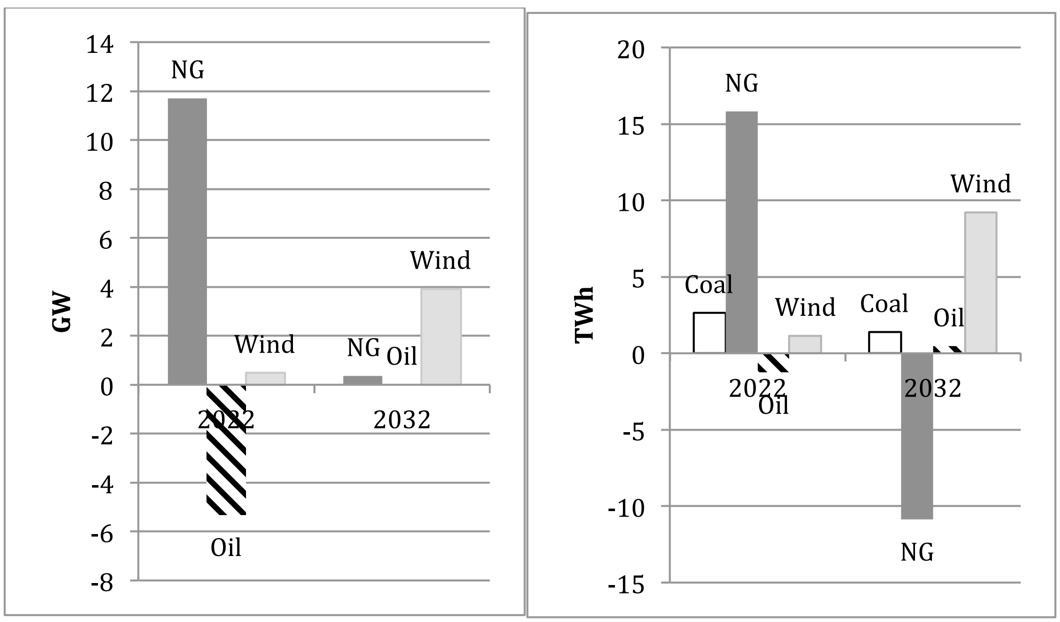


FIGURE 1.22: Generation in the Wind Incentives Case



FIGURES 1.23 and 1.24: Capacity and Generation Changes in the Wind Incentives Case

Figures 1.25-1.32 show the results of the two no nuclear cases. In 2012, the no nuclear, no regulations case is identical to the base case. Without any environmental regulations, a much larger quantity of new generation is needed, so the system builds more natural gas capacity and decommissions less oil capacity. Although the same quantity of coal capacity is used as in the base case, slightly more coal and oil generation occurs, and much more natural gas generation. When nuclear plants are decommissioned and the proposed Kerry-Lieberman law is applied, the system behaves in a similar manner, though the magnitude of changes from the base case is less. There is more natural gas capacity and oil capacity than the base case and the original Kerry-Lieberman case, but less than the no nuclear case with no regulations. Likewise, there is less natural gas generation than in the no nuclear, no regulations case, but more than in the base case and the original Kerry-Lieberman case. Coal capacity and generation also declines, almost as much as in the original Kerry-Lieberman case in 2032, though not quite as much in 2022.

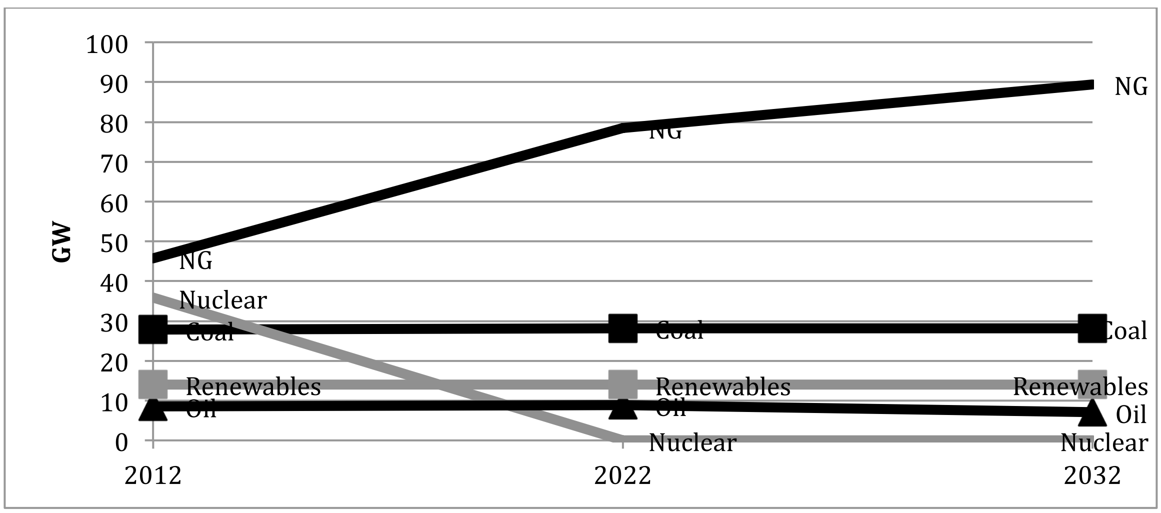


FIGURE 1.25: Capacity in the No Nuclear, No Regulation Case

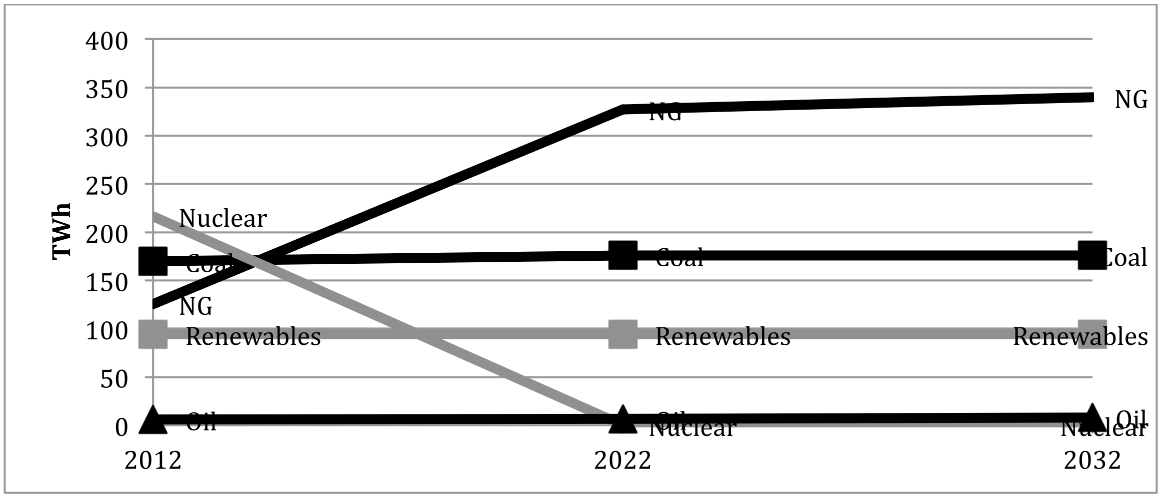
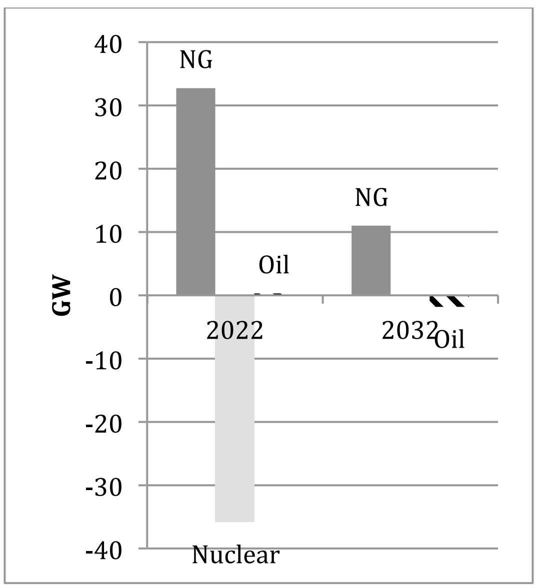
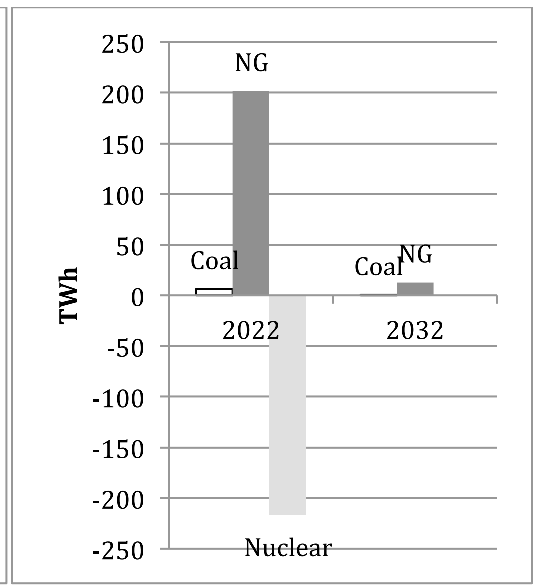


FIGURE 1.26: Generation in the No Nuclear, No Regulation Case





FIGURES 1.27 and 1.28: Capacity and Generation Changes in the No Nuclear, No Regulation Case

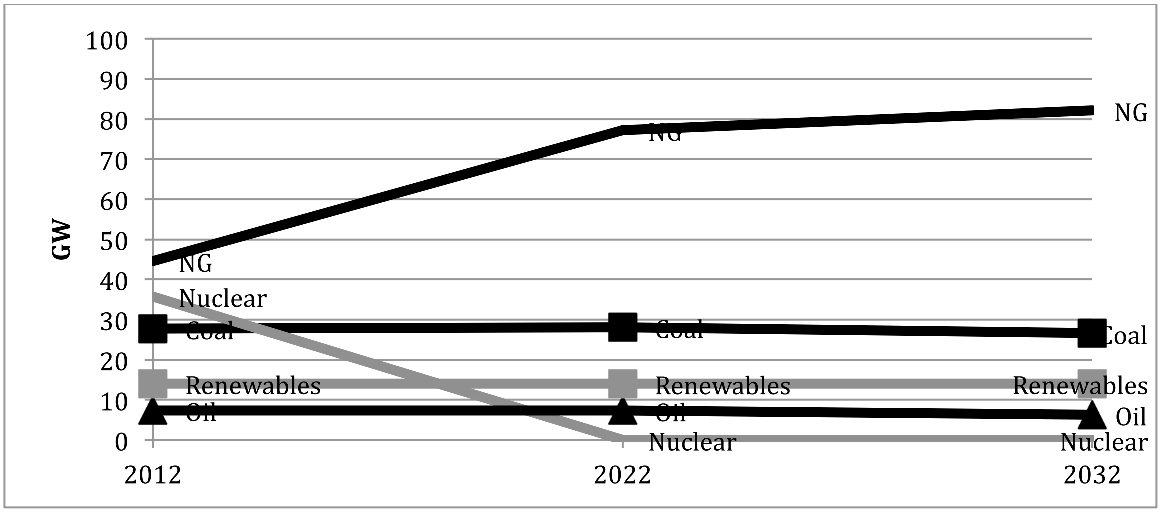


FIGURE 1.29: Capacity in the No Nuclear, Kerry-Lieberman CO2 Case

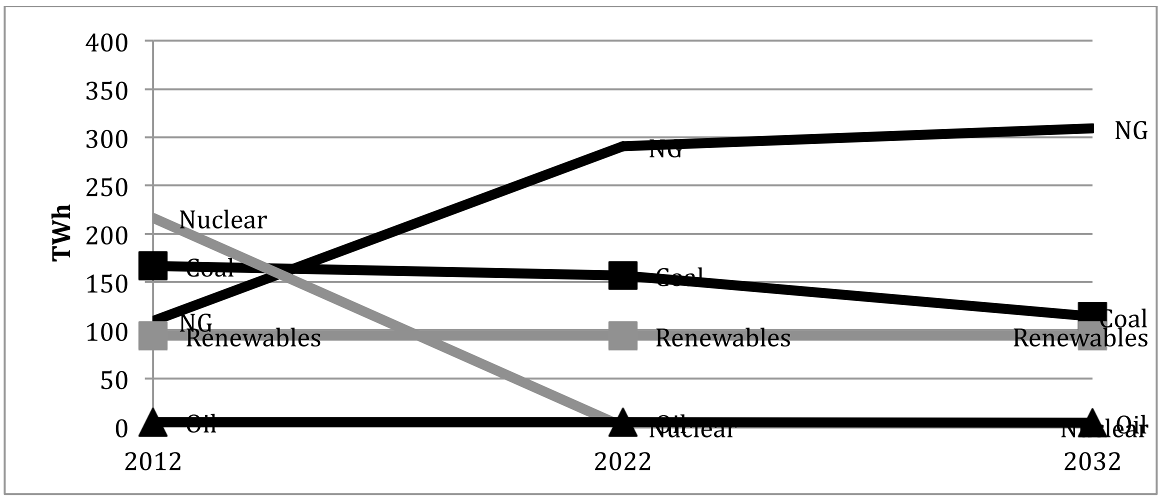
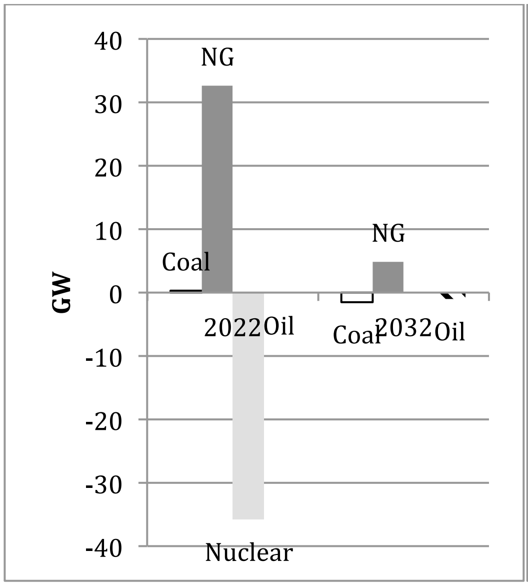
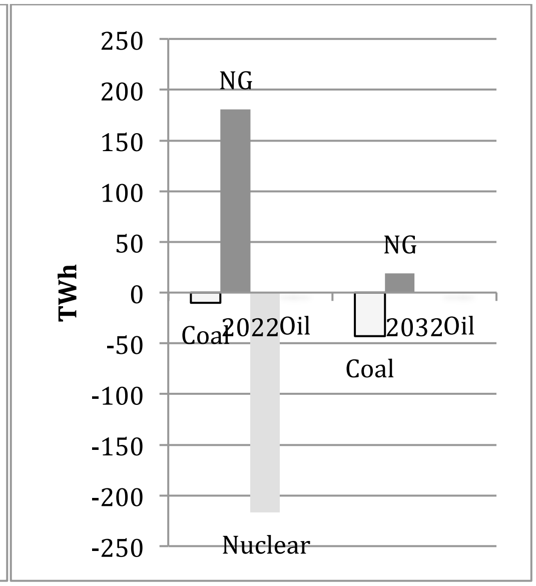


FIGURE 1.30: Generation in the No Nuclear, Kerry-Lieberman CO2 Case





FIGURES 1.31 and 1.32: Changes in Capacity and Generation in the No Nuclear, Kerry-Lieberman Case

Next, Figures 1.33-1.37 compare all these cases to each other. In these figures, the order of the labels is the same as the magnitude of each line in 2032. In Figure 1.33, total demand is plotted for each case, and for the no demand response case to illustrate the level of load abatement due to increasing prices in each case. Note that the origin is not at zero, but rather 500,000 TWh. Starting from the base case, wind incentives and no regulations are almost identical, though the wind case has a little more demand and generation, because prices are somewhat lower due to wind subsidies in some low-demand hours. The PHEV case has more demand than the base case due to the fact that load filling at off-peak hours does not much affect prices but does add to total demand. The no nuclear and no new regulations case has higher prices than the base case, which drives demand down somewhat, though as new generation is brought online, the differences in prices are reduced and demand recovers. Demand is nearly static for the marginal damages case because demand response due to price increases nearly balance out the natural load increases. Finally, the Kerry-Lieberman cases have the lowest load, because they experience the highest prices and thus the most demand response.

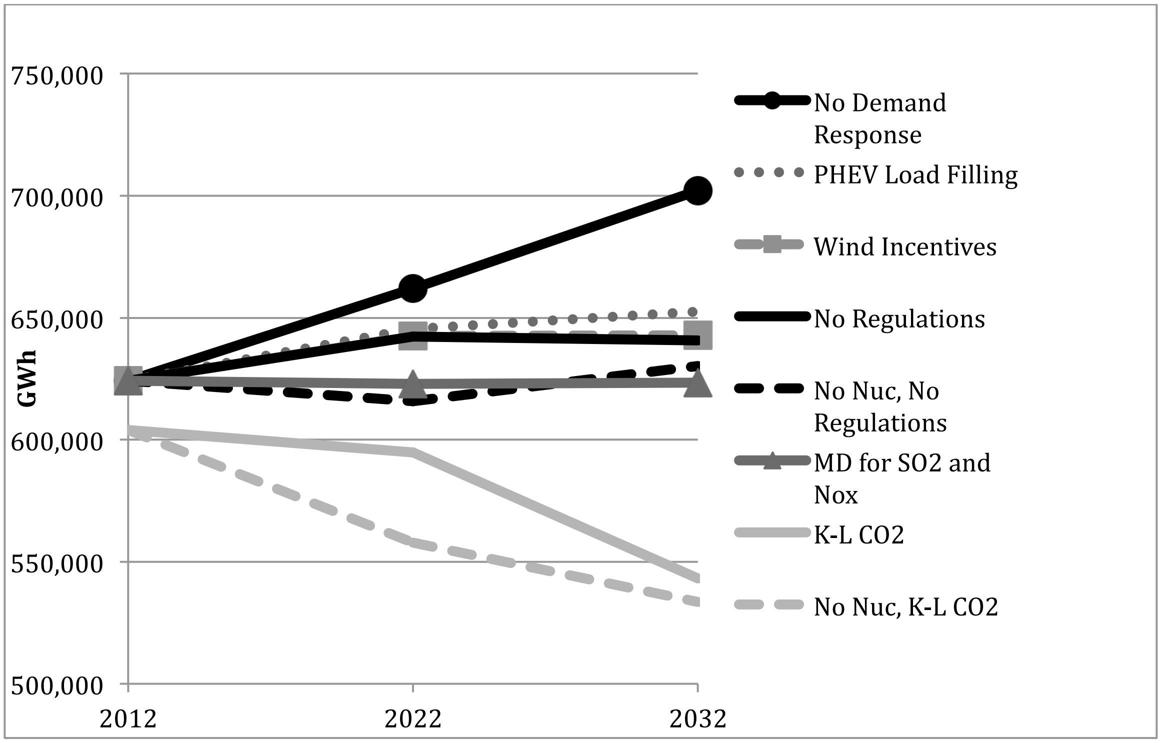


FIGURE 1.33: Total Demand

Figure 1.34 shows total capacity, which is broadly similar to total demand. Again, the origin of this Figure is at 100 GW to help differentiate the capacity paths of the various cases. The no demand response line shows how much new capacity is avoided due to demand response, in this case anywhere from 5 GW in the wind incentives case to 19 GW in the no nuclear Kerry-Lieberman case. Wind incentives have the next highest capacity, because so much wind capacity is built due to the incentives, which results in lower prices, higher demand, and thus higher capacity. The PHEV and the base cases have nearly identical capacity, because very little new capacity is needed to provide more generation at low-demand hours. The remaining cases all require less capacity because increased prices have reduced load, and thus capacity. This is especially true at summer peak hours. If the very expensive marginal oil units are brought online, summer peak prices may increase from \$300/MWh to \$1,000 MWh, resulting in a great deal of demand response, and thus less new capacity additions, since the summer peak drives capacity additions. The no nuclear cases both experience sharp declines in 2022 as nuclear plants are decommissioned, though both recover as new capacity is brought online, demand response lessens, and the need for new capacity increases.

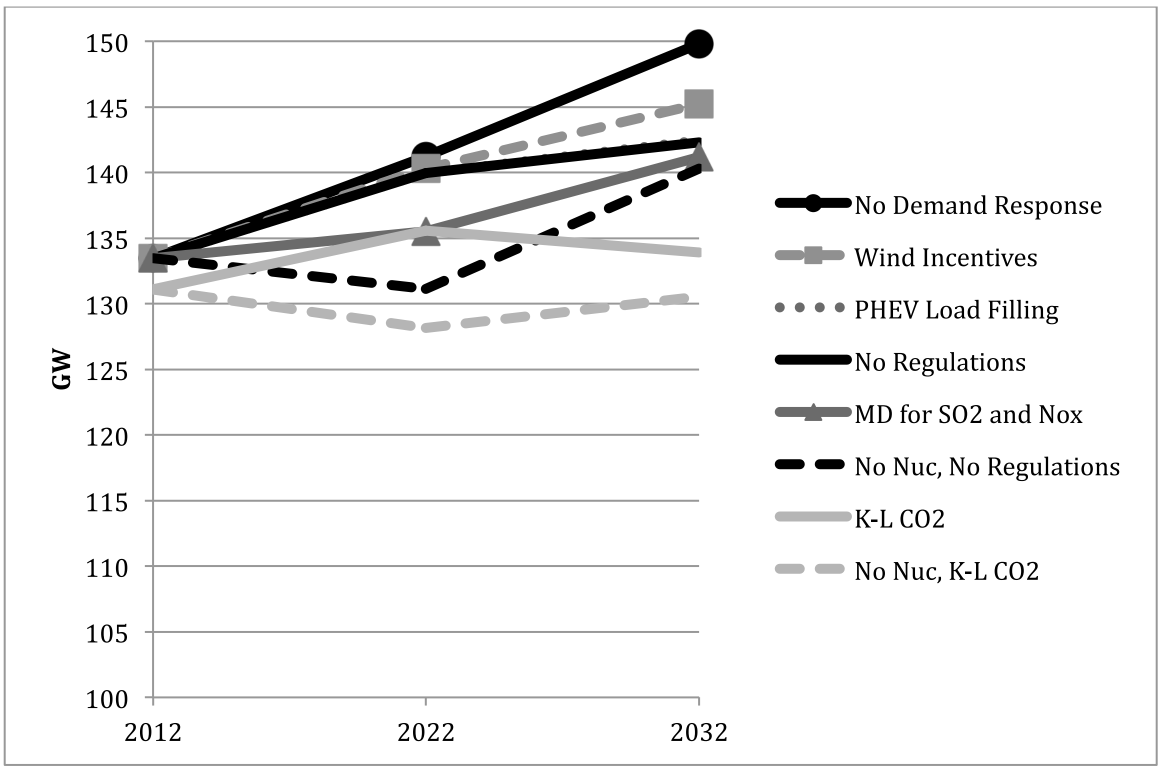


FIGURE 1.34: Total Capacity

Figure 1.35 shows average wholesale prices (weighted by load across busses and hours across representative hours.) Note again that this figure does not have an origin at zero to highlight the differences between the cases. The PHEV, no regulations and wind incentives all have low prices, with wind incentives having the lowest prices due to wind subsidies lowering the cost at some hours. Removing nuclear plants without imposing new regulations leads to slightly higher prices than imposing marginal damages in 2022, but the addition of new capacity reverses that trend in 2032. This is similar to the total demand results because total demand is essentially a function of average wholesale prices. Finally, the Kerry-Lieberman cases increase average wholesale prices the most, with the no nuclear case increasing prices more than the case with nuclear generators, because more fossil fuel units are needed, driving up the price of the marginal unit to more expensive coal and oil units, depending on the load profile.

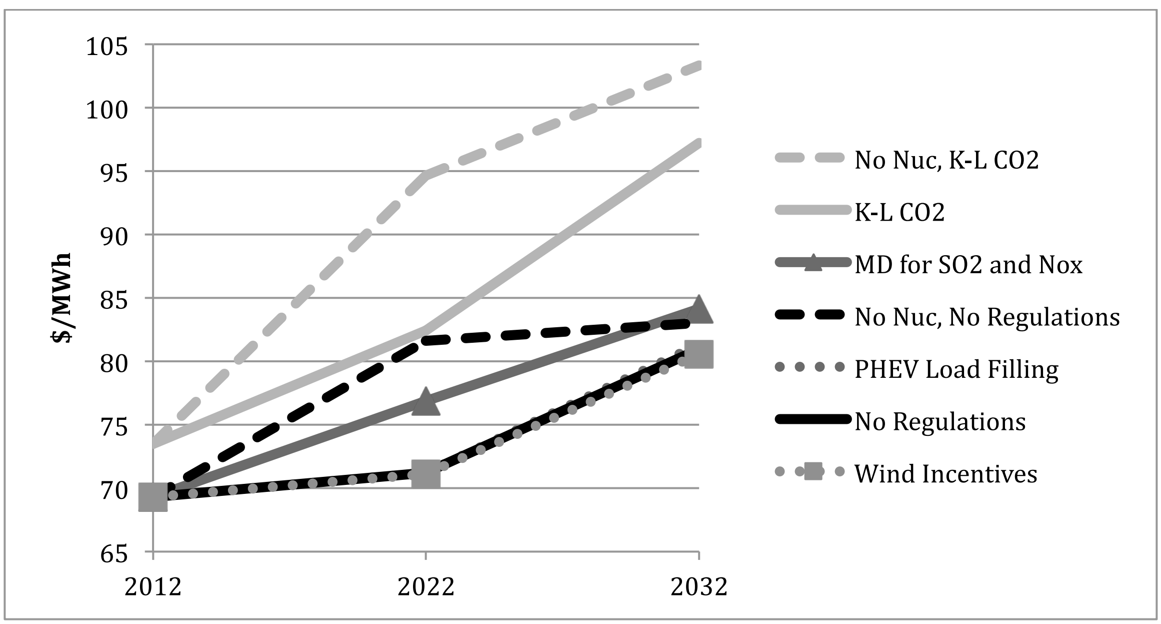


FIGURE 1.35: Average Wholesale Prices

Figure 1.36 shows CO_2 emissions for each case. Even with no regulations, CO_2 emissions decrease slightly as coal generation is replaced with more efficient and cheaper natural gas generation. Although the PHEV case has more total generation, taking into account the effect of displaced gasoline-powered cars, the total CO_2 emissions decline relative to the base case. Likewise, the wind incentives case has emissions slightly below the base case, as increased wind generation displaces some fossil fuel generation, even though there is more total generation because of slightly lowered prices. Removing nuclear plants produces a dramatic increase in CO_2 emissions, although with Kerry-Lieberman rules in place, these emissions drop below the base case by 2032. With the Kerry-Lieberman rule, CO_2 emissions are at the Kerry-Lieberman emissions cap in 2022, with prices just below the price cap, but by 2032, CO_2 emissions exceed the CO_2 cap and CO_2 prices at the cap. Finally, and most surprisingly, the case most effective at reducing CO_2 emissions is the marginal damages case, which does not directly affect CO_2 emissions at all. However, it does make operating coal plants much more expensive than natural gas plants, which drives fuel-shifting and new investment to a much greater degree than Kerry-Lieberman does.

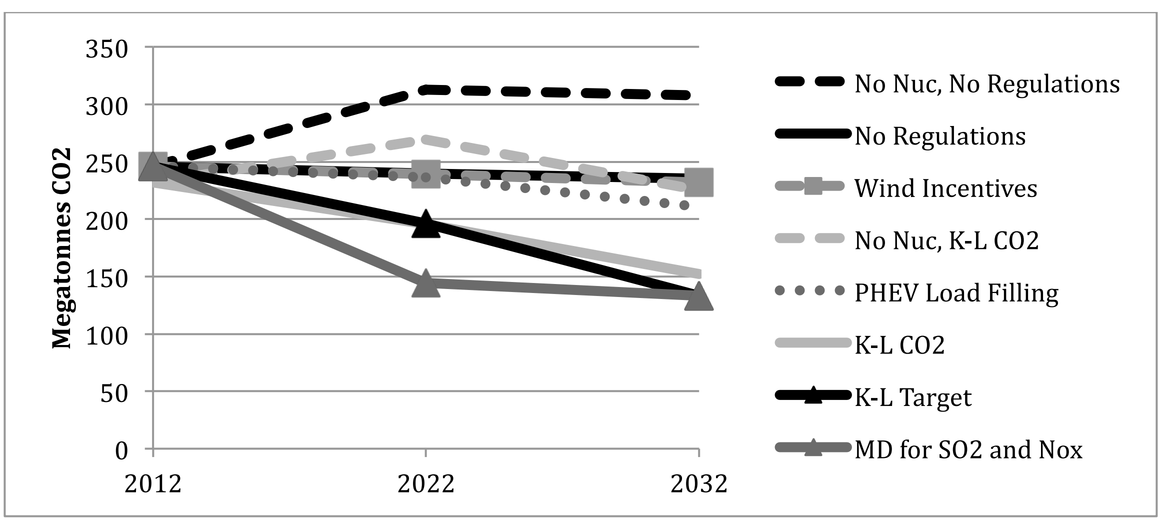


FIGURE 1.36: CO_2 Emissions

Figure 1.37 shows the expected number of lives saved relative to the base case for each case. The plug-in hybrid case is excluded because of insufficient information about the number of deaths avoided due to retiring conventional automobiles; displaying the results from just the generation would (incorrectly) show that the PHEV case caused more fatalities than in the base case. Mortality from power plant emissions is mostly caused as SO_2 and NO_X emissions create fine particulate pollution at receptor sites. At the low end of the chart, removing nuclear plants without imposing new regulations is expected to kill approximately 100 people a year. Taking just one plant offline, for example, Indian Point, would be expected to kill about 9 people a year. The proposed Kerry-Lieberman CO_2 bill, with and without nuclear plants, does a better job of saving lives as generation shifts from the more harmful coal plants to the less harmful natural gas plants. Finally, charging marginal damages saves over 2,000 lives every year, as coal generation is driven to less than 20% of base levels by 2032.

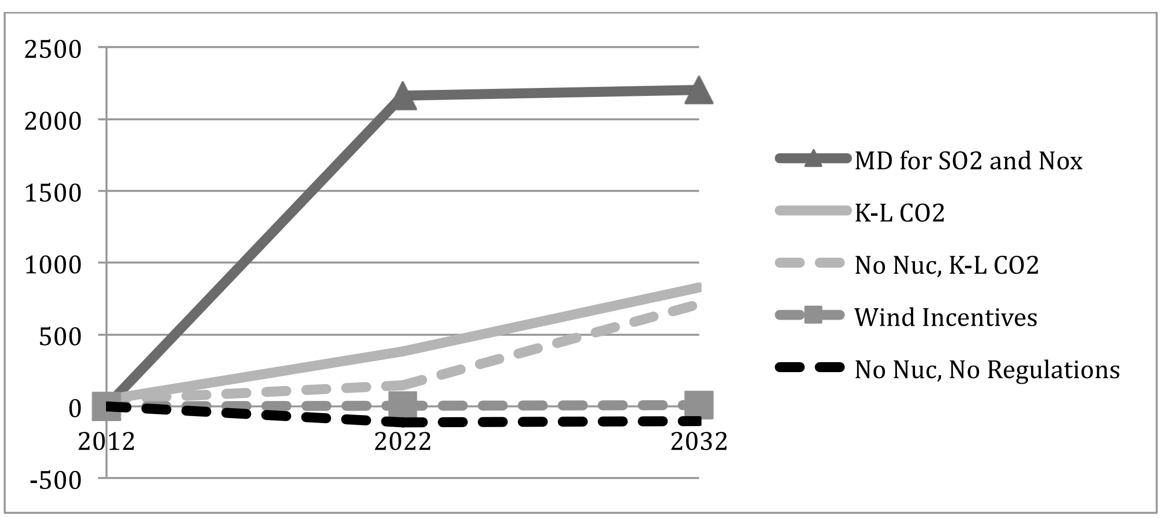


FIGURE 1.37: Expected Number of Lives Saved Compared to the Base Case

Figures 1.38-1.41 show the results of the best guess case. Aspects of both the wind incentives and the Kerry-Lieberman cases can be seen in the best guess case. There is more investment in and generation from wind generating units than in the wind incentives case, probably because of the additional incentives for less-polluting generation created by the Kerry-Lieberman price caps on CO_2 in 2022 and 2032 and the EPA's Cross-State Air Pollution Rule. As well, there is increased demand at low-load hours because of the PHEV load filling in those years. There are slightly lower levels of oil and coal capacity and generation than compared to the Kerry-Lieberman case, and slightly higher levels of natural gas. These changes are likely due to the new EPA rule, which place high prices on the SO_2 and NO_X emissions that characterize coal plants. The EPA price forecasts for the Cross-State Air Rule used here are probably not accurately modeled – in the EPA's modeling, there are only small changes in power generation, while in this simulation, coal generation falls by over 40%. The reductions in SO_2 and NO_X are smaller in the Northeast than the new rules require, although the NPCC has less coal-fired generation, and a greater proportion of emissions reductions would be expected to come from the Midwest and southeast.

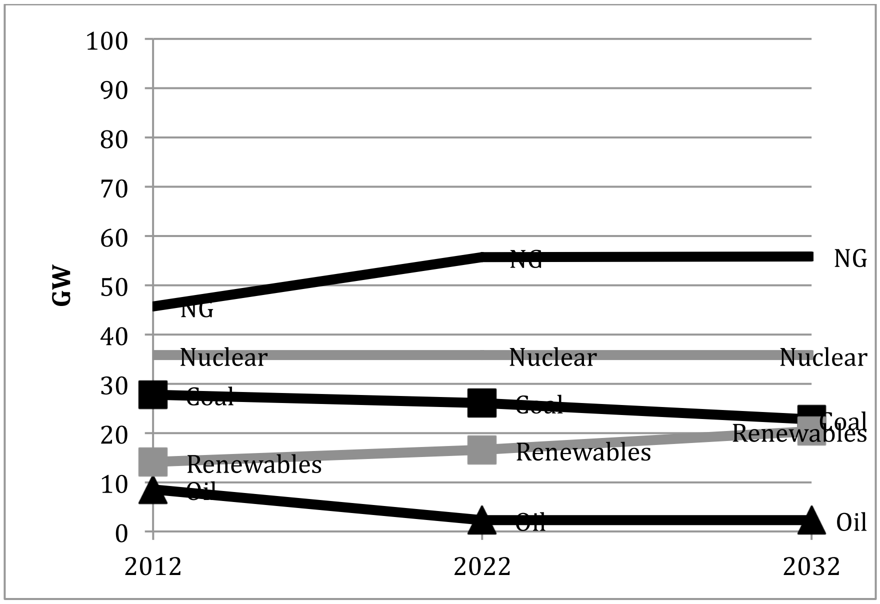


FIGURE 1.38: Capacity in the Best Guess Case

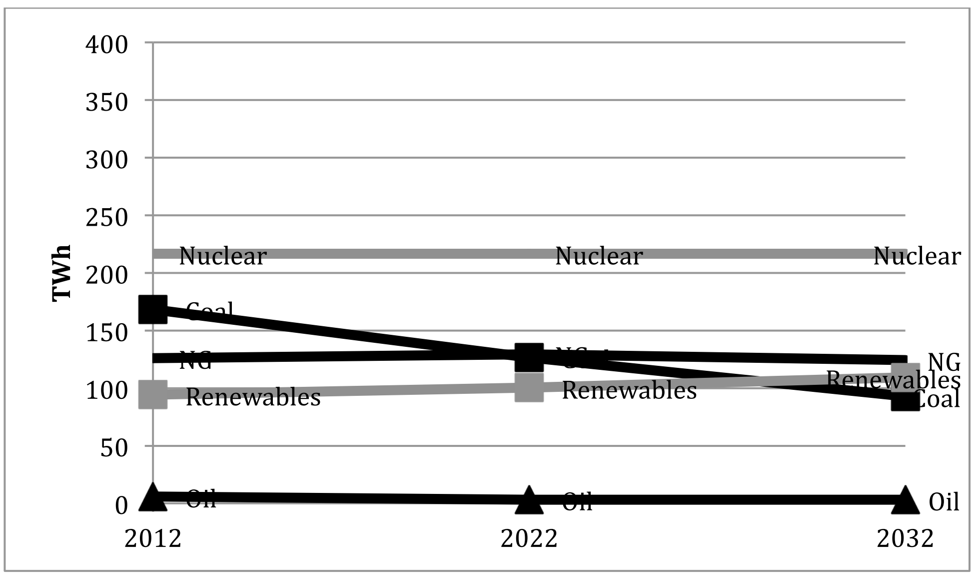
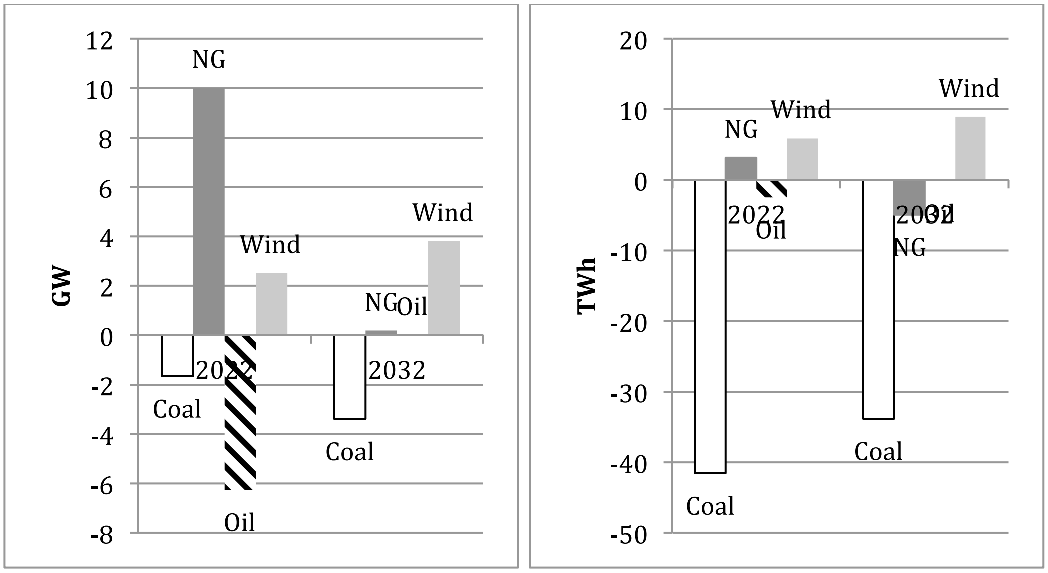


FIGURE 1.39: Generation in the Best Guess Case



FIGURES 1.40 and 1.41: Capacity and Generation Changes in the Best Guess Case

Figures 1.42-1.45 show the results from the socially optimal case. As in the marginal damages case, natural gas capacity increases rapidly and coal is almost completely eliminated from the system. The addition of the social cost of carbon reduces total generation, despite the addition of PHEV, relative to the marginal damages case by about 6%. No wind capacity is built in this case, either, so wind generation is only built in the presence of incentives for wind, even in the presence of prices for all three pollutants. Coal capacity is also slightly lower than in the marginal damages case, likely a result of the addition of a carbon price.

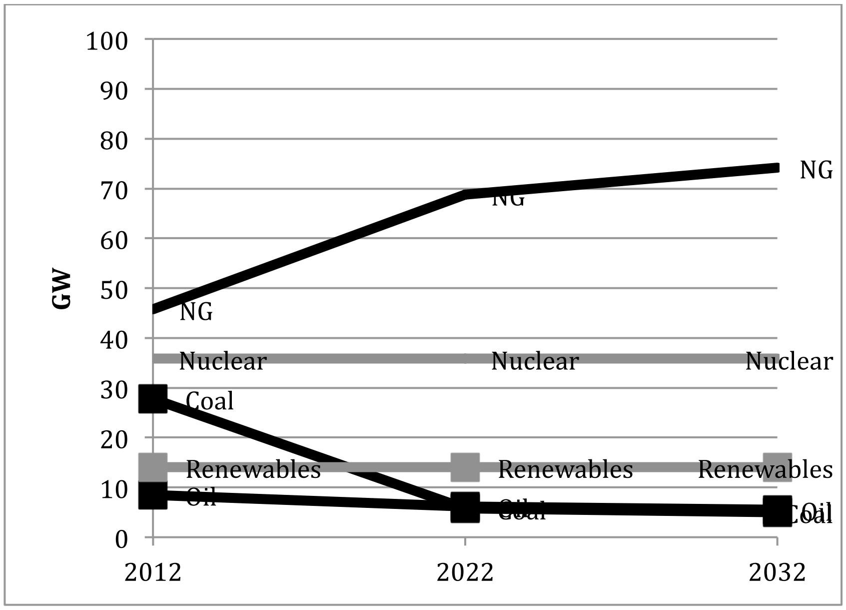


FIGURE 1.42: Capacity in the Socially Optimal Case

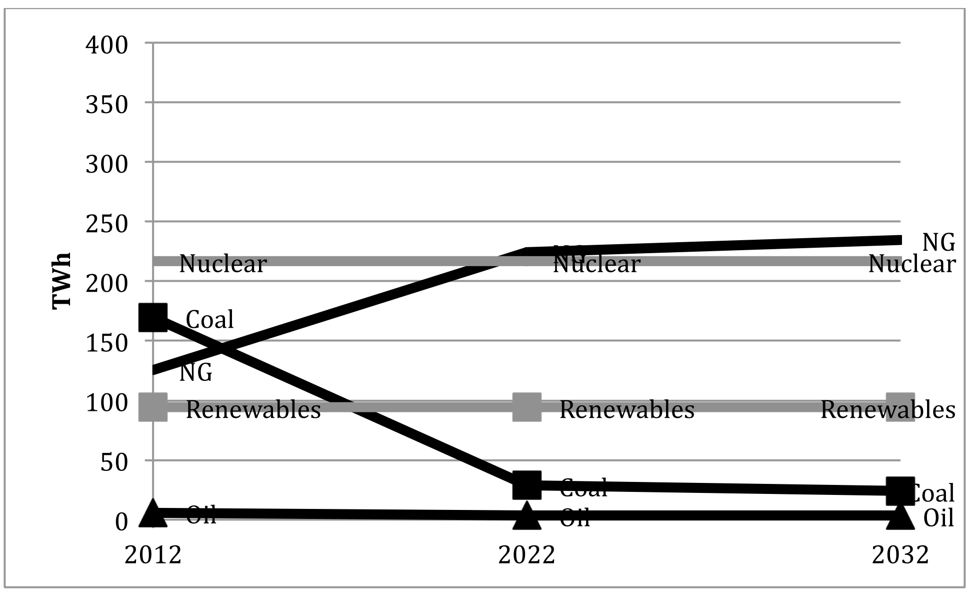
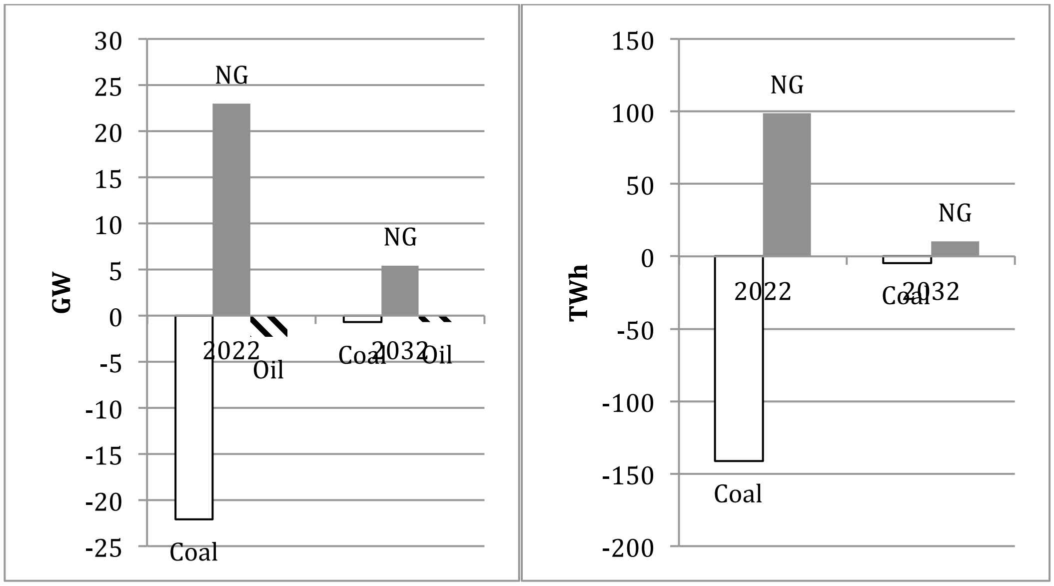


FIGURE 1.43: Generation in the Socially Optimal Case



FIGURES 1.44 and 1.45: Capacity and Generation Changes in the Socially Optimal Case

Finally, Figures 1.46-1.48 compares the results of the best guess, socially optimal and base cases in terms of average wholesale prices, CO_2 emissions, and expected number of deaths per year. Both cases have higher average wholesale electricity prices than the base case, though neither dominates the other for the entire time period, and the difference are not large. The prices from these two cases rival the Kerry-Lieberman case, and are only exceeded by the no nuclear Kerry Lieberman case. The socially optimal case has by far the lowest CO_2 emissions, beating the marginal damages case, 20% lower in 2022 and almost 40% lower in 2032. The best guess case is lower than the Kerry-Lieberman case, and it is even below the Kerry-Lieberman CO_2 cap and the marginal damages emissions in 2032. When it comes to the last comparison, the socially optimal case results in the most lives saved of any case, including the original marginal damages case. These estimate for lives saved are also a lower bound, because lives saved from reduced automotive emissions are not yet accounted for in this model.

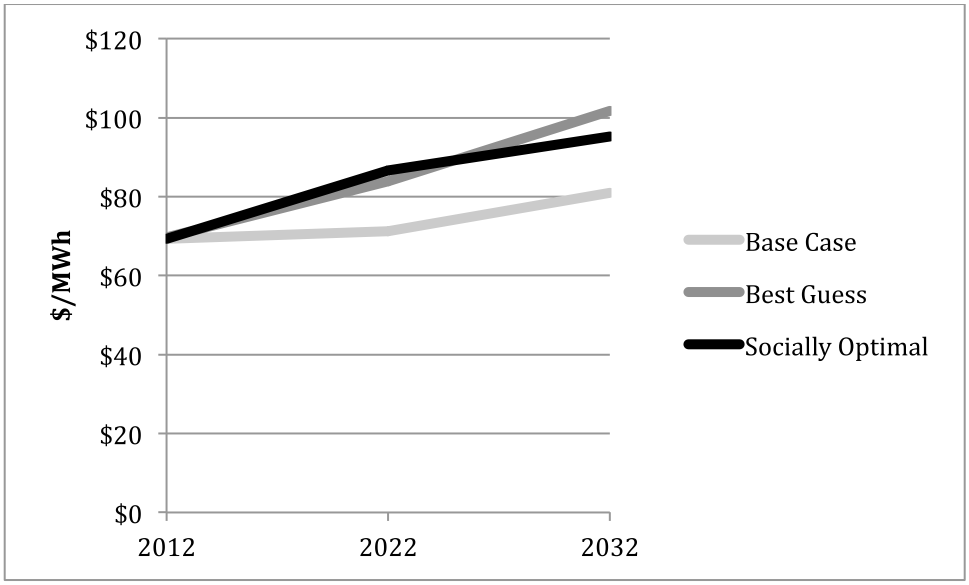


FIGURE 1.46: Average LMP in the Best Guess, Socially Optimal and Base Cases

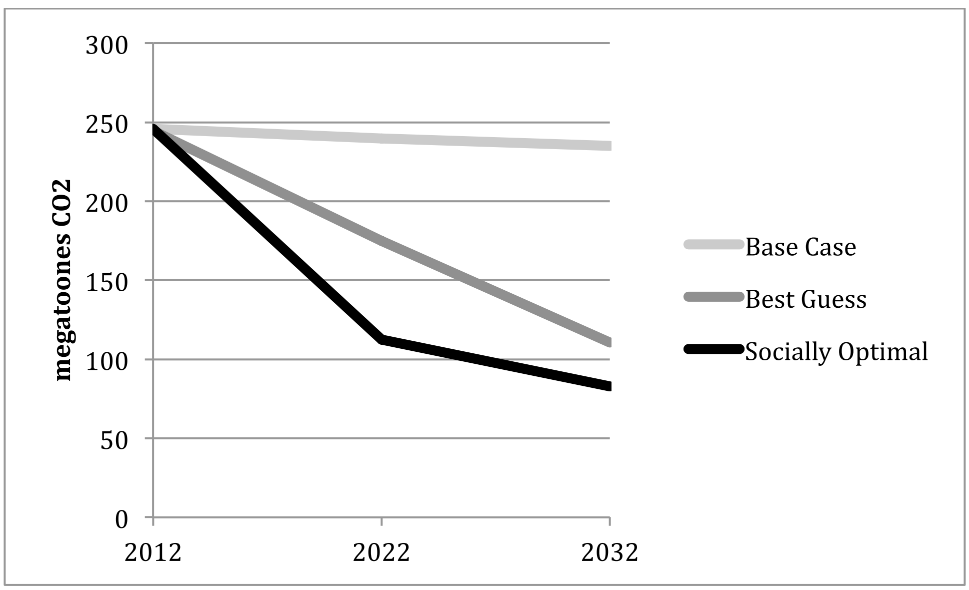


FIGURE 1.47: CO_2 Emissions in the Best Guess, Socially Optimal and Base Cases

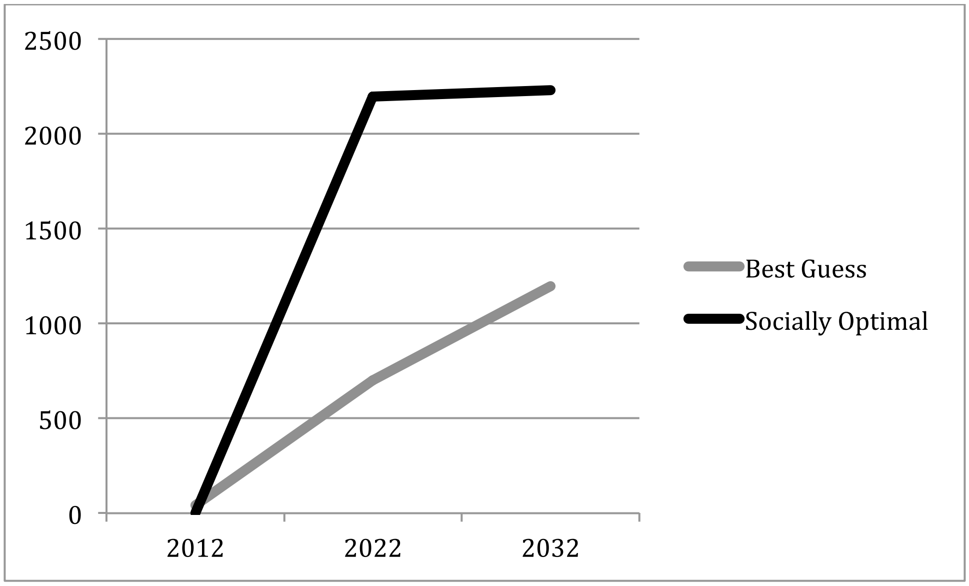


FIGURE 1.48: Lives Saved Per Year Relative to the Base Case

V. Conclusions

Using a transmission-constrained model with actual generator data is essential for estimating impacts to the electric grid from large-scale policies. Transmission and generation constraints are a factor for all of the analyses in this paper, and provide a more realistic picture of the effects of policies than the "bubbles and pipes" models commonly used which neglect intra-region transmission constraints and greatly simplify inter-region transmission.

Looking at the policies in this paper, three facts stand out. First, demand response is incredibly important for accurately modeling the electric grid. Demand response can have a very large impact on CO_2 emissions and load, while having a relatively smaller impact on prices. Second, natural gas combined cycle seems to be the future of power plant construction, if forecasts for natural gas prices and construction costs for plants are accurate. Unless wind is subsidized, natural gas combined cycle plants are superior to every other type of generation in terms of annual costs with or without new emissions regulations, whether CO_2 or marginal damages. Finally, charging marginal damages for SO_2 and NO_X is the most effective policy for saving lives, reducing CO_2, and results in lower prices than strict carbon-reducing policies such as the proposed Kerry-Lieberman bill.

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CHAPTER 2

CARBON LEAKAGE AND THE REGIONAL GREENHOUSE GAS INITIATIVE: AN ANALYSIS WITH A TRANSMISSION-CONSTRAINED REDUCED NETWORK ELECTRICITY MODEL

John Timothy Taber[6]

ABSTRACT

There are a number of national energy models used for investment planning and studying the effects of proposed environmental policies on the electric grid. No model to date has included data about actual generators, a network model for the electric grid, and emissions. In this study, the SuperOPF, a full AC optimization/simulation framework with optimal investment developed at Cornell University is used to study the effects of regulations on the Northeast power system. The Northeastern power system is represented by a simplified system of 36 nodes, which offers a compromise between computational tractability and accuracy, particularly in modeling the limits on important inter-system transmission lines.

In this paper, I analyze the effects of a regionally-limited carbon cap and trade program, the Regional Greenhouse Initiative (RGGI), when additional generating assets in non-affected states are included in the analysis. In the face of different carbon prices on generating assets in covered and non-covered states, generation is

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expected to shift from states bound by RGGI to states outside of RGGI. This carbon leakage may undermine some or all of the benefits of RGGI while simultaneously increasing prices for customers in the area. Even though carbon prices under RGGI are very low, some leakage is occurring, and this leakage will worsen if carbon prices increase. Ultimately, a unified policy offers greater carbon reduction at a lower cost, which would increase popular acceptance of such policies. Information from an online contingent-valuation survey is combined with the results of the electrical model to estimate willingness to pay for carbon abatement under different scenarios.

I. Introduction

The Regional Greenhouse Gas Initiative (RGGI) is a collection of northeastern states that have set up a carbon cap and trade system with the intention of limiting and ultimately reducing carbon emissions in New England, New York and part of the PJM Interconnect[7]. However, the power grid in these states is not isolated from the rest of the country. Because electrons and power flows obey physical laws separate from economic and political desires, increasing the costs of generation in the RGGI states may increase imports of power, particularly from unregulated fossil fuel units outside of RGGI. Thus, the impact of CO_2 emission prices in the RGGI states on total CO_2 emissions may be lessened when the total system emissions are considered. An increase in CO_2 emissions outside of a regulated area in response to regulation is often

[7] The PJM Interconnect is a Regional Transmission Organization named for three of its principal states: Pennsylvania, New Jersey and Maryland. It has expanded to include all or parts of 13 states and the District of Columbia, from Michigan to North Carolina.

called "leakage." Currently, RGGI has no plans to deal with leakage, and due to the Commerce Clause, it may be impossible to stop this shift of power at all.

Although the expected cost of CO_2 in RGGI is not expected to be very high, it is important to consider the effect of higher prices than those found as a result of RGGI, because other policies may lead to higher prices. For example, proposed national cap and trade programs for CO_2 (such as the Waxman-Markey bill, also known as the American Clean Energy and Security Act of 2009) may result in very high carbon prices, on the order of $100/ton or more. CO_2 prices under the proposed Kerry-Lieberman bill (also known as the American Power Act) may exceed $50/tonne by 2026. As Canadian units will not be incorporated in these US national policies, results from this analysis of RGGI may be illuminating as to the degree of leakage expected. This model can also be used to estimate the impact states joining or leaving RGGI, as New Jersey has done at the start of 2012.

Several studies of the effects of emissions programs have been conducted using other planning models, which are used to estimate the effects of policies on the electric grid. For example, the EPA has used ICF's Integrated Planning Model (2011) to examine the impacts of air emissions policies on the U.S. electric grid, including the Cross-State Air Pollution Rule and the Transport Rule. However, while the IPM does have very detailed information about every generator in the United States including information about emissions for various pollutants, its transmission model lacks essential details. The ICF breaks the continental United States down into a few dozen regions for analysis. Within each region, transmission is unconstrained, and power flows between regions are constrained by aggregate flow limits. This model ignores the structure of the electric grid entirely, replacing it with a “bubbles and pipes” model for ease of analysis.[8] The Resources for the Future Haiku model (Paul and Bertaw 2002) also uses constraints between regions to model flow limits, and uses “46 model plants” to estimate generation technology. These planning tools are useful, but may fail to capture the full impact of new policies because they ignore the realities of the electric grid.

Most studies of carbon leakage have focused on general equilibrium effects resulting from trade in finished goods, and only a few studies have examined the effects of a bi-regional carbon cap and trade policy. A study by Chen (2009) finds that for a DC model of a small part of the PJM system, which is part of RGGI, carbon leakage may approach 90% of abatement in the control area. This study does not include investment and only models a small portion of the region, which may overstate the impact of leakage. Fowlie (2009) uses an oligopoly with two crude transmission constraints to represent California. She shows that this bi-regional policy achieves only a third of the emissions reductions as a unified policy with double the emissions cost.

The remainder of this paper is organized as follows. In the next section, I provide an overview of the optimization problem solved to optimize investment and generator dispatch. A description of the network model for the electric grid and the information about the generators is also provided. In the third section, I review the

[8] A bubbles and pipes model breaks the electric grid into regions – bubbles. Within each region, flows are unconstrained, and between each region, there is a single “pipe” with a flow limit standing in for all flow between the regions. Because power flows over all lines available for use, intraregional flow limits may limit interregional flows. Power flows into New York state are often limited by intraregional flows to New York City from other regions in New York, not intraregional lines from Canada or New England.

results of the simulation for the carbon leakage cases. The fourth section discusses the results of a novel online contingent valuation experiment from which information about willingness to pay is drawn. The fifth section presents a unified model to illustrate various levels of acceptance for bi-regional and unified carbon cap and trade programs. Conclusions and discussions are provided in the final section.

II. Model Description and Data

To simulate actual real electricity generation and capacity investment in a power market, the following optimization problem is solved:

$$\max_{p_{ijk}, I_{ij}, R_{ij}} \{\sum_i \sum_j [(\sum_k H_k(B_{jk} - (c_i^F + a_{jk}e_i)p_{ijk})) - (c_i^T(p_{ij}^0 + I_{ij} - R_{ij}) - c_i^I I_{ij})]\}$$

$$\begin{aligned} \text{subject to} \quad & \\ p_{ij}^0 + I_{ij} - R_{ij} &\geq p_{ijk} \\ p_{ijk} &\geq \alpha_i^{min}(p_{ij}^0 + I_{ij} - R_{ij}) \\ K_{ij} &\geq I_{ij} \\ \sum_j L_{jk} &= \sum_i \sum_j p_{ijk} \\ &\textit{DC network constraints} \end{aligned}$$

i: generator index
j: node index
k: representative hour index
p_{ijk}: aggregate real power output from generator i at node j during representative hour k
p^0_{ij}: existing generator capacity
R_{ij}: capacity retirement
I_{ij}: capacity investment
c^F_i: cost of fuel, operations and maintenance per MWh
c^T_i: cost of taxes and insurance per MW
c^I_i: annualized cost of new investment

H_k: hours system is at load profile k
e_i: emissions vector for generation type I, tonnes/MWh
a_{jk}: emissions cost vector at node j in hour k, \$/tonne
$\alpha^{min}{}_i$: min generation for type i
K_{ij}: max investment in fuel type I at node j
B_{jk}: Benefit function for demand response
L_{jk}: Net load

The objective function aims to maximize the net benefits of the value of generation minus the sum of power and fixed costs, subject to active power flow equations and transmission, generation, voltage and other constraints.[9] Since we are using a DC approximation of an AC system, we can ignore costs and constraints involving reactive power and voltage angles. A DC approximation is a good model for these purposes (Schulze, 2009), and also ensures the problem is linear, which aids in computational tractability.

Each year is split into sixteen representative hours: four representative hours for each season. Figure 2.1 shows the percentage of the year modeled by each representative hour. The summer representative hours make up a greater portion of the year relative to the other seasons because in this model, summer comprises more months than any other season: May through September, which coincides with the EPA's Ozone Season under the Cross-State Air Pollution Rule. The fall and spring

[9] This step of the analysis was performed using the SuperOPF and MATPOWER, a collection of MATLAB M-files for solving "stochastic, contingency-based, security-constrained optimal power flow[s]." The MATPOWER home page can be found at: http://www.pserc.cornell.edu/matpower. The SuperOPF is still under development. In terms of the terminology in the SuperOPF, the different representative hours are treated as contingencies from the base case (summer peak), and the Positive Active Reserve Price is the fixed cost or the investment cost, depending on if the generator is an existing unit or a new (potential) unit. Since we are representing an entire year with each contingency instead of the normal time frame of the SuperOPF, ramp rates are unimportant, and each generator has ramp rates equal to its maximum power output. However, to keep coal plants from cycling on and off between seasons, their minimum contracted power is set to 15% of PMAX.

hours comprise two months each: October and November, and March and April, with the remaining three months falling into the winter category.

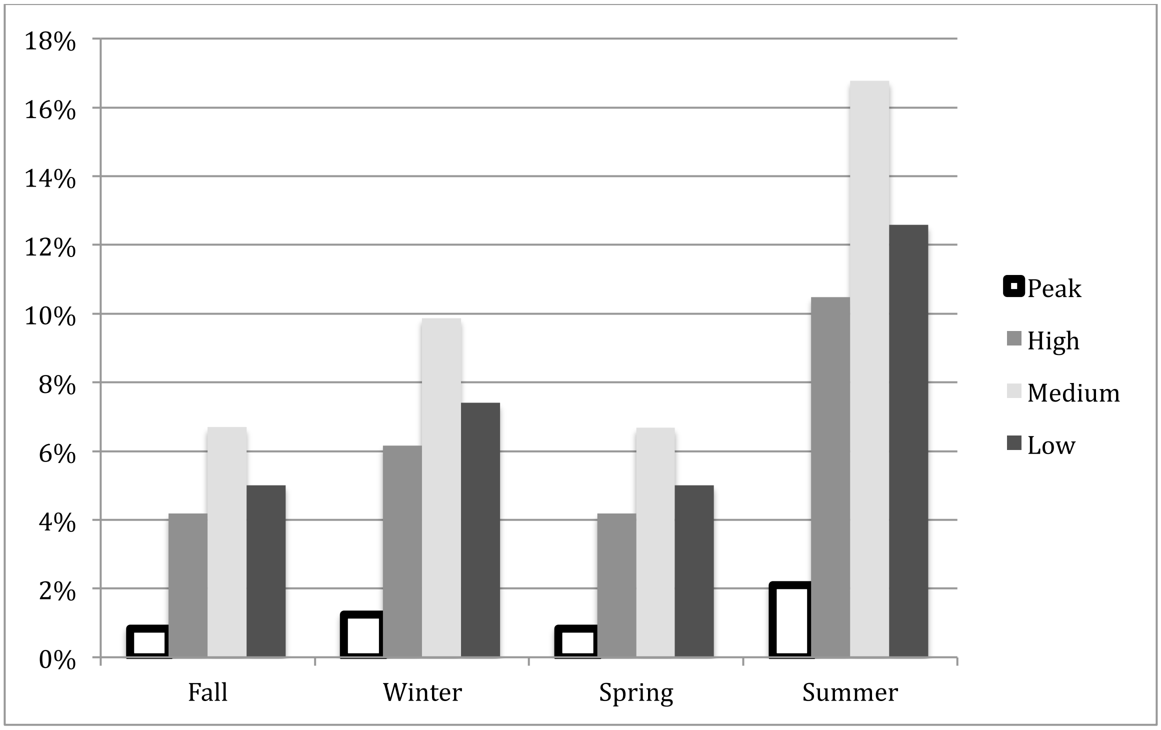

FIGURE 2.1: Relative Frequency of Representative Hour Types

Each representative hour is modeled as a deviation from the base case (Summer Peak). Generators can be de-rated, to reduce their maximum power capacity, load can be scaled (separately for each area in the model) and different emissions costs can be applied. Figure 2.2 presents an average of the load scaling across all regions for each representative hour. The Summer Peak has the highest total system demand. Most regions experience their peak demand at the summer peak due to summer cooling needs. The Maritimes in Canada, however, actually has its annual peak during the winter. Investment in units, especially new units needed to meet this peak demand (often called peaking units), is driven by this representative hour. Although the summer peak represents only a small portion of total hours, there must be enough capacity on hand to provide for this demand, since storage on a utility scale is prohibitively expensive with current technology. In the real world, there exist peaking units that are only used for a few hours for a few days each year, usually on hot afternoons in July and August.

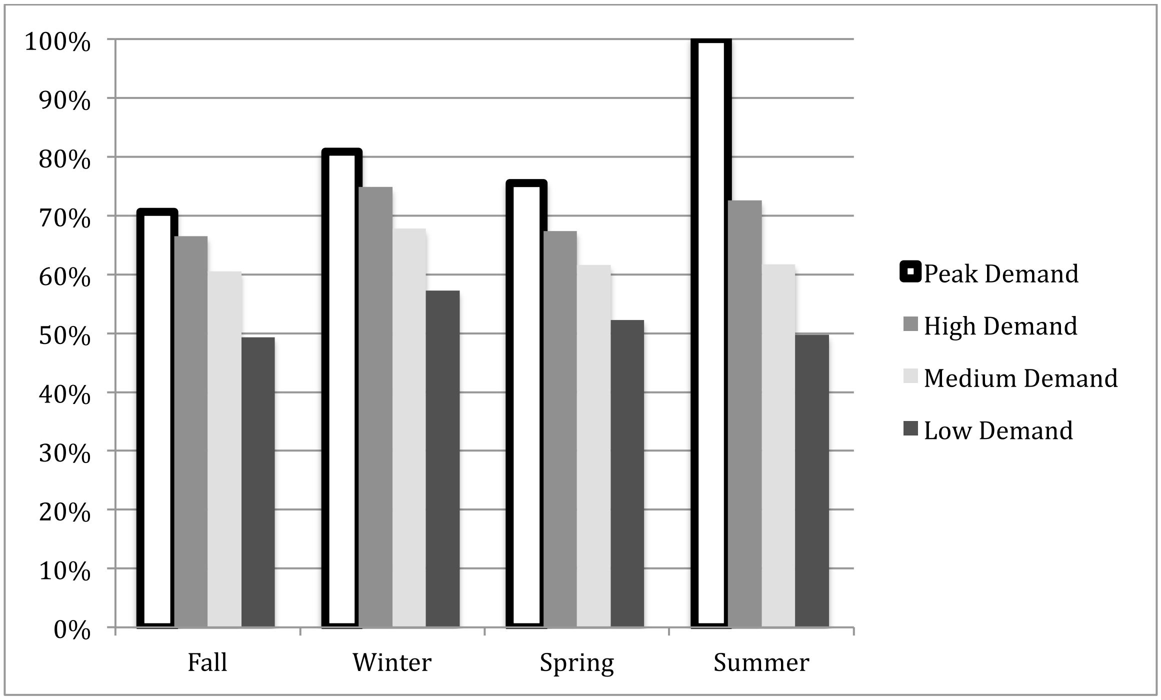

FIGURE 2.2: Average Demand Assumptions for Representative Hour Types

Accurate modeling of costs arising from emission policies is central to the accuracy of this paper. Many emissions laws in the United States propose cap-and-trade programs, which operate by putting a cap on the total amount of emissions, distributing emissions allowances, usually by endowment or auction, and establishing a permit market with a price for these permits. A firm that expects to exceed its emissions allotment based on the number of allowances it owns may reduce emissions or purchase additional permits. Firms are expected to minimize the costs of these two options to maximize their profits. A cap-and-trade program, like an emissions tax (which places a tax on each unit of emissions), puts a price on each unit of emissions. Examining the response of the power industry to a price on emissions allows us to predict the effect of a cap-and-trade program as well as an emission tax program. The term "emissions price" is used to refer to either the permit price in a cap-and-trade program or the emission tax rate. Firms that are endowed with permits should still value their opportunity cost even if they represent windfall earnings.

The structure of emissions programs in the United States was changed drastically in 2010 following the issuance of the Transport Rule by the EPA, which almost immediately caused the price of SO_2 permits in the Acid Rain Program to fall to near zero by replacing the Clean Air Interstate Rule. The Acid Rain Program has been succeeded by four separate trading programs under the Cross-State Air Pollution Rules. For the purposes of the leakage analysis, only New York, Pennsylvania and New Jersey are affected, and three different emissions policies must be modeled: annual SO_2, annual NO_X and seasonal (summer) ozone. According to EPA estimates, affected units will pay $1,000/ton of SO_2 in 2012, rising to $1,100/ton in 2014. Annual NO_X emissions will cost $500 in 2012, rising to $600 in 2014. During the summer ozone season, affected units will pay $1,300/ton of NO_X in 2012 and $1,500/ton in 2014. The first two policies are included by increasing the cost function in equation (2) for all affected units, while the final policy is modeled by increasing the cost function for affected units only during the four summer representative hours. As with most regulations affecting power generating units, only units with a generation capacity greater than 25 MW are affected. (Which in itself may produce some leakage, though that is not the focus of this paper.) Interestingly, these new rules may serve to mitigate some of the leakage resulting from RGGI, since generating units in Pennsylvania and New Jersey will have to pay for these permits, but other generating units in New England do not.

Information about fixed and investment costs for generation plants, as well as information about operating costs for new plants was obtained from the Energy Information Administration (2011). Four types of new plants were selected to be built: dual unit advanced pulverized coal, advanced natural gas combined cycle, dual unit nuclear, and onshore wind. These four plants represent efficient versions of four of the most common types of electric power used in the United States for which investment is possible. The overnight cost reported by the EIA was converted into a total cost by assuming an equal portion of the overnight cost was spent at the beginning of each year, and the debt accrued interest at an annual rate of 8%. A power plant can be expected to pay back its investment in the first 10 years of operation, so a capital recovery factor was calculated using equation (4).

$$CRF = \frac{i(1+i)^n}{(1+i)^n - 1} \tag{4}$$

CRF: Capital Recovery Factor
i: Interest Rate (8%)
n: Compounding Periods (10 Years)

For ten years and an annual interest rate of 8%, a plant is built if it can cover 14.9% of the total construction cost in the first year of operation. Generation costs assume prevailing rates for fuels are the same as the average in the region for 2010: \$5.56/thousand cubic feet for NG and \$2.82/MBTU for coal. In line with DOE estimates, natural gas prices increase by about 20% in 2022, and a further 23% in 2032. Coal prices decrease slightly (98% of 2012 costs) in 2022, and increase 4% from that value by 2032. Total capacity additions are limited to 15% of the maximum rate in a 5-year period in which each type of fuel has, historically, been built. This corresponds to the NPCC's share of total US electrical generation. For example, between 1985 and 1990, approximately 34 GW of nuclear capacity was built in the United States. Thus, 5 GW is a conservative upper limit for the nuclear capacity that could be built by 2022 in the NPCC. Information about new construction is summarized in Table 2.1.

TABLE 2.1: Information about New Generators

Fuel Type	Capital Recovery/Year \$/MW	Total Variable Cost \$/MWh	Total Possible Capacity Additions
Coal	\$497,201	\$29.05	10 GW
Natural Gas	\$181,824	\$39.05	32 GW
Wind*	\$392,322	\$0	3.5 GW
Nuclear	\$1,141,454	\$2.04	5 GW

*Wind assumes an average capacity factor of 33%, excluding federal and state incentives.

The distribution of demand and the tradeoff between fixed and variable cost drives the investment and maintenance of different kinds of units. For example, roughly 30% of the year has an expected load at about half of peak load: The low demand case for each season in Figures 2.1 and 2.2. (And the entire year has a demand at half of peak load or more.) For a power plant running 8,760 hours a year, total costs for an average fossil-fuel plant range from a low of \$356,000/MW for a coal plant to over $2.5 million dollars/MW for an oil plant. However, if a plant is only running for the summer peak, 184 hours a year, the average natural gas plant costs under $28,000/MW to operate, cheaper than any other plant type except for hydropower.

This analysis uses a network reduction of the Northeastern United States developed by Allen, Lang and Ilic (2008.) A diagram of this network is shown in Figure 2.3. Each point on this diagram represents a bus in the network, which are both numbered and named by the independent system operator or planning authority. The spatial layout of the busses roughly corresponds to their geographic location. The two lone busses at the top of the figure are Hydro Quebec and New Brunswick. The five busses at the left side correspond to Ontario, which connect into the western New York System. The entire middle of the diagram and the bottom right correspond to busses in New York, which connect to Pennsylvania and New Jersey (at the bottom left) and New England (at the middle right.) The lines connecting these busses correspond to the actual or equivalenced lines in the real world. In this work, Allen et al reduced the Northeast Power Coordinating Committee area to a 36 bus[10] model, while maintaining important line flow constraints. Data on existing generating units, provided by Energy Visuals, came from the 2006 reliability planning process of the Multiregional Modeling Working Group, and includes data on units projected to be operational in the summer of 2008. In addition to information about fixed and variable costs, the model also has information about CO_2, SO_2 and NO_X emissions rates for each power plant. For more details about this process, see Schulze et al

[10] A bus is one node on the network, usually containing both load (customers) and generating units and connected to other busses via transmission lines.

(2009.) Information about the physical location of each plant was used to determine whether the RGGI CO_2 prices would be applied. Plants at busses in New England, New York, Maryland and Delaware are part of RGGI. Those in Canada, Pennsylvania are not. New Jersey is currently part of RGGI, but has announced intentions to leave by the end of 2011. Models were run both with New Jersey included and excluded from RGGI.

The benefits function for demand response is based off the long-run elasticity and growth rates for elasticity. As electricity prices increase, whether due to natural growth of the system, or to added costs to generation from emissions prices, people will respond by cutting back their level of power consumption. In the long run, the elasticity of demand for electricity is approximately -1 (Dahl, 1993). However, recent research suggests that, even in the short run, the elasticity of people responding to average prices (ie, utility bills) is -0.982 (Fell et all, 2011). Since each step of our model represents 10 years, an elasticity of -1 is used to represent demand response. Average distribution costs are assumed to be $70/MWh. In the NPCC, the average LMP for the base year is also $70/MWh. Thus, $140/MWh is a good estimate for retail prices. A 2.5% reduction in demand would be expected as prices increased to $143.50, or an increase in LMP from $70 to $73.50. Because this optimization problem must remain a linear program, demand response is represented in ten blocks, each representing 2.5% of total load. The effective price for each block of demand response is at the midpoint of each interval.

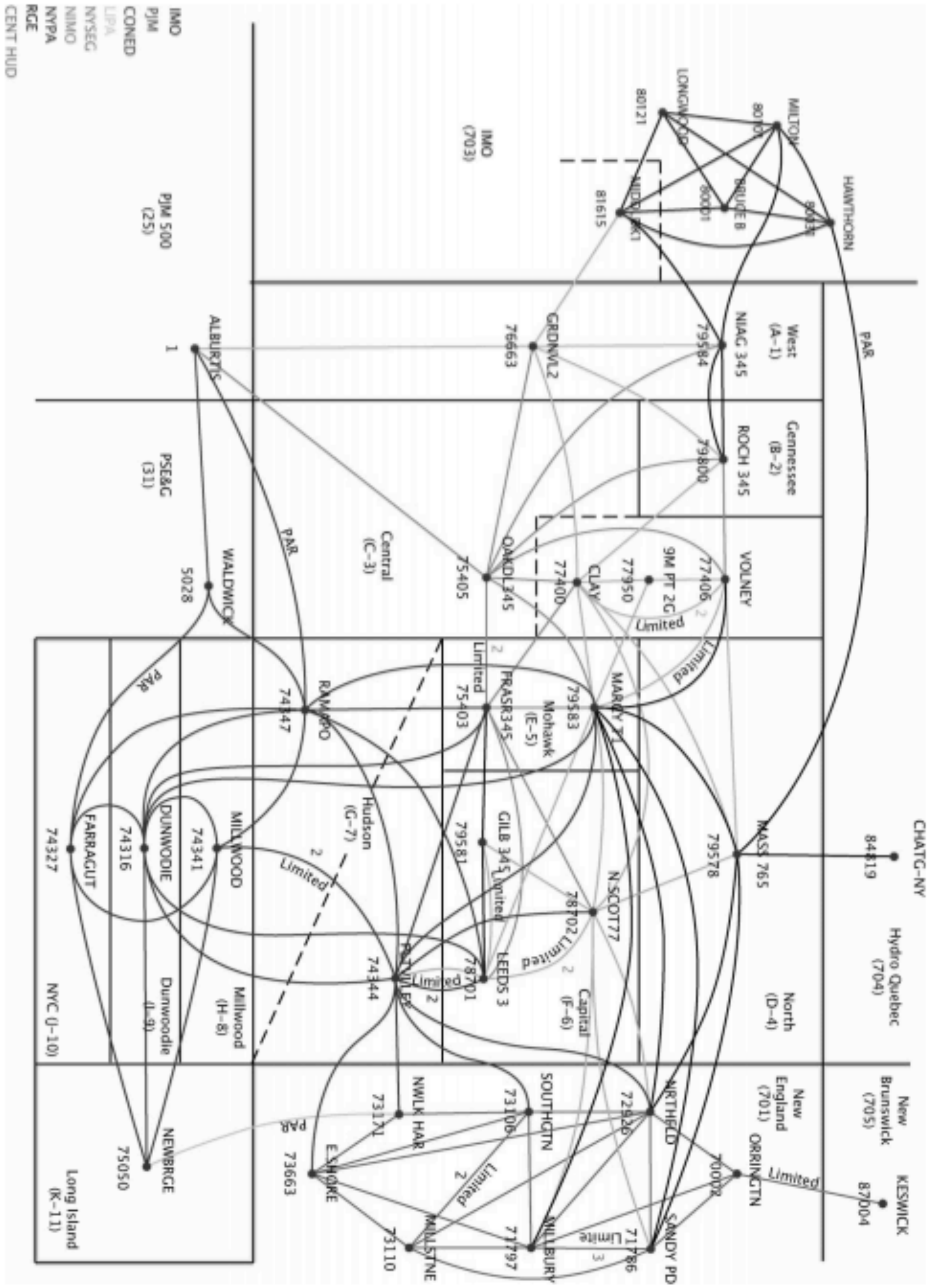

FIGURE 2.3. Diagram of 36-bus model from Allen et al (2008).

III. Carbon Leakage

The Regional Greenhouse Gas Initiative (RGGI) is a collection of states and provinces in the Northeastern United States and Canada that have set up a regional cap-and-trade system for CO_2 emissions. Ten states are participants in RGGI, meaning they take part in the emissions cap-and-trade market, while Pennsylvania and several Canadian provinces are observers. One of the participant states, New Jersey, has announced plans to leave RGGI by the end of 2011. The states and provinces involved in RGGI are depicted in Figure 2.4. The aim of the Regional Greenhouse Gas Initiative is to first stabilize carbon emissions from 2009-2014, then gradually decrease the emissions cap from 2015-2019 until a 10% reduction is achieved. However, because of increases in energy efficiency and the recent recession, emissions are already below past levels, and it is the price floor on permits rather than the emissions cap that determines prices for CO_2.

FIGURE 2.4: Map of RGGI States

To model the effect of bi-regional and unified carbon dioxide policies over time on total carbon dioxide production, a number of scenarios were simulated. To estimate the effects of varying CO_2 prices on carbon leakage in RGGI, CO_2 prices of \$0 to \$100/tonne were applied to units in RGGI in \$5 increments. The same CO_2 prices were also applied to all units, to compare the cost of emissions reduction for bi-region model versus a unified emissions market. These analyses were both done in 2012 and 2022, allowing one investment cycle. To estimate the effects of the EPA rules and New Jersey leaving RGGI, a number of additional simulations were run. These simulations are summarized below.

The columns of Table 2.2 vary the emissions rules applied to RGGI. Four cases are simulated, with two CO_2 prices for RGGI, \$0 and \$1.89/tonne, and two applications of the new EPA rules, whether they are present or not. LMP is locational marginal price, and is the marginal price of electricity at each node in the network. Because of transmission constraints, electricity prices can vary across the network. Average LMP is a load and duration weighted average of prices across the network for a year. The first column in the table, \$1.89 RGGI CO_2, EPA Rules, is the best prediction for the state of the NPCC in 2012. The other columns can be used to estimate the effect of the RGGI cap and trade program and the new EPA rules. Compared to having no regulations, CO_2 emissions are expected to be 4.22 megatonnes lower, though emissions will be about 4.46 megatonnes lower in RGGI, which means that 240,000 extra tonnes of CO_2 are produced in the non-affected units, and 5% of emissions reductions are undone by leakage. The EPA regulations and RGGI have a synergistic effect. Both policies together reduce CO_2 more than the sum of each policy individually, while wholesale prices (LMP) increase less than the sum of increases for either policy. The EPA rules also reduce leakage: leakage is 6% of RGGI CO_2 reductions in the \$1.89 RGGI and EPA Rules case, but 20% in the RGGI price alone case. Of course, as CO_2 prices increase, the difference between generator prices inside and outside of RGGI will increase, while the price of SO_2 and NO_X may stay relatively stable if emissions are switching from covered SO_2 and NO_X units inside of RGGI to outside of RGGI.

TABLE 2.2: Summary information about the effects of variations in environmental regulations on CO_2 emissions

	\$1.89 RGGI CO_2	\$1.89 RGGI CO_2	\$0 RGGI CO_2	\$0 RGGI CO_2
	EPA Rules	No EPA Rules	EPA Rules	No EPA Rules
Total CO_2 (Megatonnes)	241.74	244.15	244.63	245.96
RGGI CO_2 (Megatonnes)	98.14	100.31	101.9	102.6
Average LMP \$/MWh	70.17	69.63	69.67	69.31
RGGI LMP \$/MWh	72.1	71.62	71.53	71.13
Total CO_2 Reduction	4.22	1.81	1.33	
RGGI CO_2 Reduction	4.46	2.28	0.69	

Table 2.3 shows summary information about the effects of New Jersey leaving RGGI at the end of 2011. The first column has New Jersey not in RGGI, and the second has New Jersey still included in RGGI. The third column has New Jersey included in RGGI for the sake of emissions prices, but not included in RGGI for tallying CO_2 emissions. This is to examine the effect of including New Jersey on RGGI emissions, while adjusting for the effect that merely including New Jersey will have on program emissions, regardless of the emissions reductions from RGGI. Including New Jersey in RGGI decreases CO_2 emissions by 140,000 tonnes, though it increases emissions by 370,000 tonnes in the rest of RGGI. Most likely, this is because the average generating unit in New Jersey produces 0.8729 tonnes of CO_2/MWh, while the average unit in the rest of RGGI produces 0.8268 tonnes of CO_2/MWh. When New Jersey is included in RGGI, some generation shifts from the

relatively more polluting units in New Jersey to other, less polluting units in RGGI. Some of the effect is also due to the slightly reduced load because of the increase in prices, both in RGGI and in the rest of the region.

TABLE 2.3: Summary information about the effects of New Jersey's RGGI status on CO_2 emissions

NJ In RGGI?	No	Yes	Yes*
			NJ CO_2 Not counted in RGGI
Total CO_2 (megatonnes)	241.74	241.6	241.6
RGGI CO_2 (megatonnes)	98.14	114.62	98.51
Average LMP	70.17	70.22	70.22
RGGI LMP	72.1	72.22	72.16

Next, this paper will look at the impact of leakage as CO_2 prices increase. Figure 2.5 illustrates the result of a range of prices in RGGI on CO_2 emissions for the entire region and the power plants in RGGI states. Although the actual emissions prices are very low in RGGI, on the order of \$1.89/tonne (the current price floor), these simulation results illustrate the leakage that may result from prices high enough to substantially reduce carbon emissions, which RGGI does not currently do. Although increasing carbon prices on RGGI units does reduce total system CO_2, there is an offsetting effect from non-RGGI units, which increase their power output and thus their CO_2 emissions. When CO_2 permit prices increase from \$0 to \$100/tonne, total CO_2 emissions drop from 244 megatonnes to 176 megatonnes, a decline of 68 megatonnes (28%.) However, RGGI emissions drop by 87 megatonnes, and non-RGGI units increase their emissions by 18 megatonnes. This leakage appears to decline as CO_2 prices increase. This decline is due to both transmission limits and generation limits. As CO_2 prices increase, two inter-region lines are at a limit: Maritimes/Maine and Ontario/New York. As well, two intra-RGGI lines in New York are at their limit. Even if sufficient transmission capacity were available, the non-covered units can only generate 68 GW of power, against a summer peak load of 120 GW, which can be reduced to as little as 90 GW with demand response. Nuclear, wind and hydropower units in the RGGI states add another 18 GW of power. Of course, even with very high CO_2 prices, efficient units in RGGI will still be dispatched. At CO_2 prices of \$100/tonne, an average natural gas plant producing 0.65 tonnes of CO_2/MWh with a cost of \$72/MWh before CO_2 prices will cost \$137/MWh to operate, much less than the average oil plant or the worst coal plant, even if no emissions prices are applied to those units.

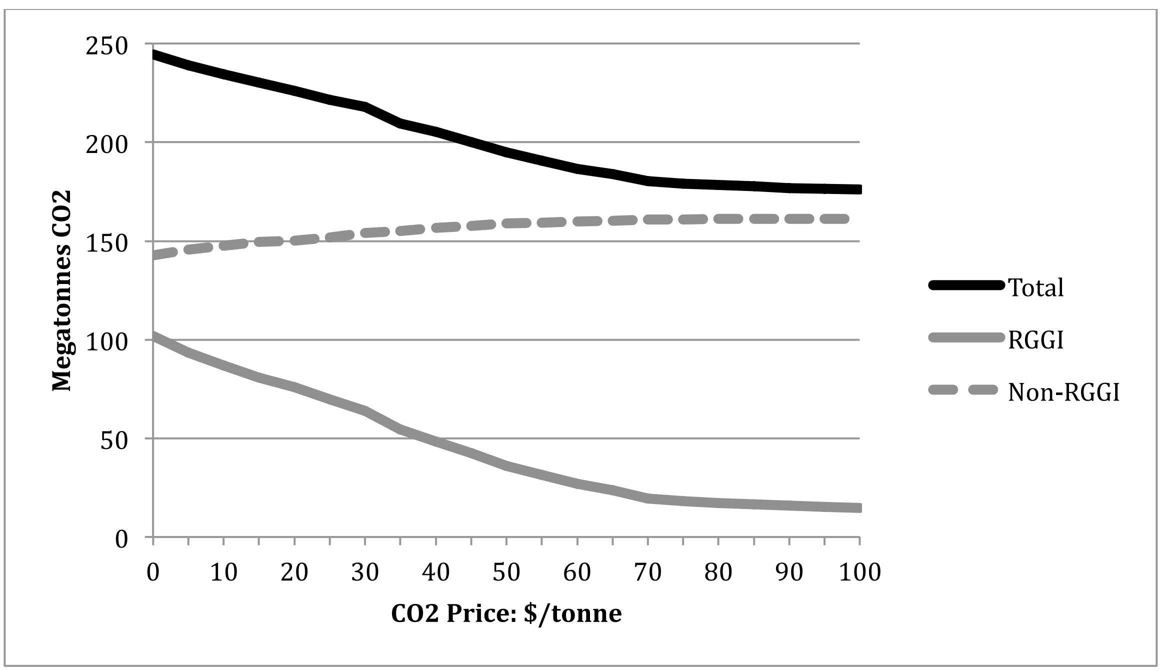

FIGURE 2.5: CO_2 Emissions from a range of CO_2 prices charged to RGGI units in 2012

Figure 2.6 shows three average cost curves for summer peak generation. The two curves for RGGI show the different amounts of generation available at \$0/tonne and \$100/tonne CO_2 prices, while the non-RGGI curve is not affected by RGGI CO_2 prices. The large vertical step before 20 GW for RGGI and 30 GW for Non-RGGI units is the point at which low-cost hydro, wind and nuclear units are fully dispatched and fossil-fuel units start to come online. For any given price of electricity, this figure would show the relative amounts of RGGI and non-RGGI capacity used (in the absence of transmission constraints.) Figure 2.7 presents total aggregate generator cost curves for three carbon prices and applications: no carbon price, a \$100/tonne RGGI price, and a \$100/tonne price on all units, along with the summer peak load, including demand response, which is why the demand curve is downward sloping between approximately \$150/MWh and \$200/MWh. Note that the LMP at summer peak is higher than the average LMP for the year, regardless of CO_2 prices. Imposing a carbon price on all units instead of just RGGI units appears to mainly shift up the bottom end of the curve, around 50 GW, while not substantially affecting prices at summer peak levels. This may mean a unified carbon cap and trade policy would have a relatively greater effect on prices during low demand hours than at any other time.

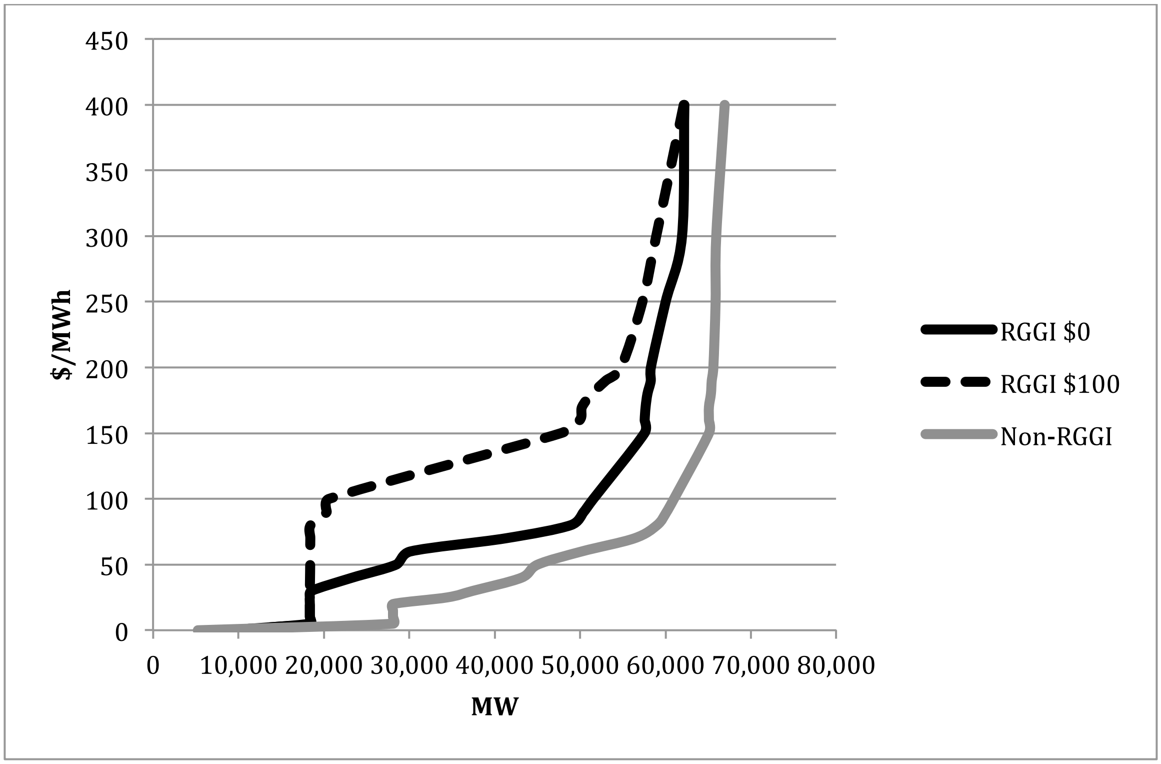

FIGURE 2.6: Aggregate Generator Cost Curves for RGGI and Non-RGGI Units in 2012

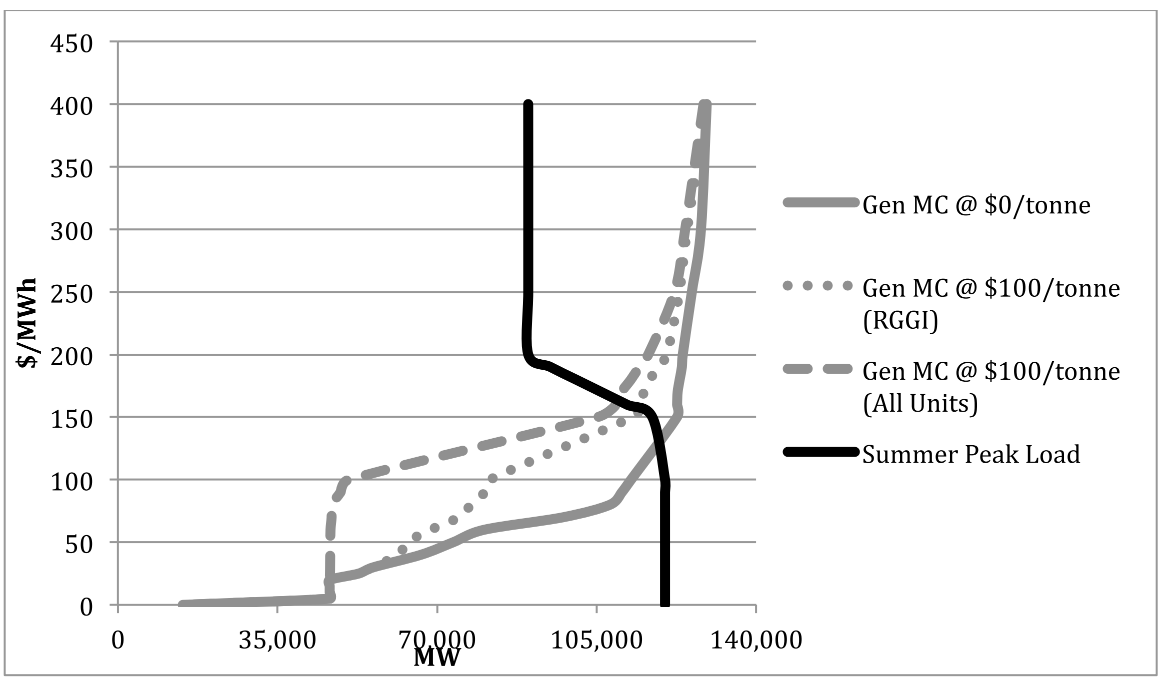

FIGURE 2.7: Supply and Demand Curves for Electricity at Summer Peak Load (In the absence of transmission constraints)

Figures 2.8 and 2.9 show how the capacity and generation of fossil-fuel sources of power in the NPCC and in RGGI change as the carbon price in RGGI increases. (Non-fossil fuel generators are not affected, as they all have very low marginal costs and are fully dispatched by the model.) The main effect of higher CO_2 prices on capacity is that less coal capacity is used starting around $30/tonne, and that all existing coal capacity in RGGI is left idle once CO_2 prices reach $70/tonne. Coal generation confirms this trend, as the slope of coal generation changes once the $30/tonne price is hit, because the decline in coal generation prior to $30/tonne is from using existing generators less, and the decline after $30/tonne is from shutting down generators. (Since any coal generator must use at least 15% of its rated maximum power at all times, coal generators can not only be used during peak demand periods.) Natural gas generation in RGGI also declines to approximately 1/3 of its $0/tonne level as CO_2 prices increase, but the change in total natural gas generation is less than the change in RGGI natural gas generation, as units outside of RGGI increase their output from 50 TWh to a max of 74 TWh at $70/tonne CO_2 prices. Non-RGGI coal generators only increase their output by 2 TWh. Most of the carbon leakage is coming as generation shifts from coal and natural gas plants in RGGI to natural gas plants outside RGGI.

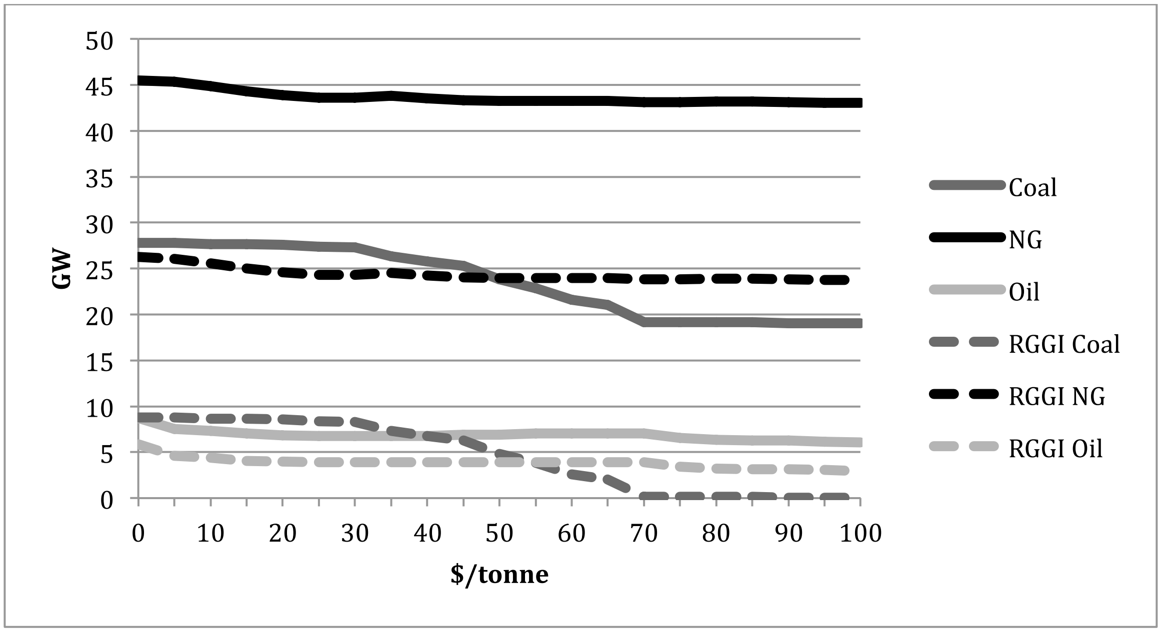

FIGURE 2.8: Fossil fuel capacity for a range of RGGI CO_2 Prices in 2012

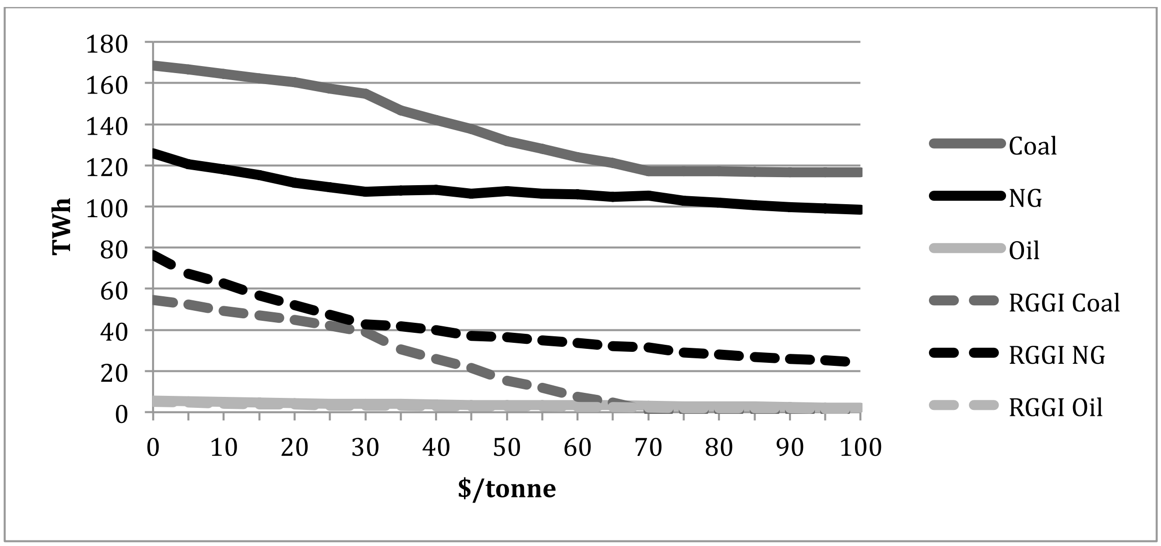

FIGURE 2.9: Fossil fuel generation for a range of RGGI CO_2 Prices in 2012

The 2022 chart of CO_2 prices versus carbon output (Figure 2.10) shows broadly similar results to increasing carbon prices when investment is allowed. The intercepts at $0/tonne are shifted downwards slightly, which shows that investment in lower-carbon generating sources happens regardless of CO_2 prices: there is 12 GW of new investment even at $0/tonne. New natural gas combined cycle units are, in addition to being cheaper to operate, relatively lower in carbon emissions. However, leakage is a larger concern when new investment is allowed. As CO_2 prices rise to \$100/tonne, RGGI emissions drop by 80.2 megatonnes, but non-RGGI emissions increase by 21.1 megatonnes. In 2012, an 87.2 megatonne drop by RGGI units only resulted in an 18.6 megatonne increase from non-RGGI units.

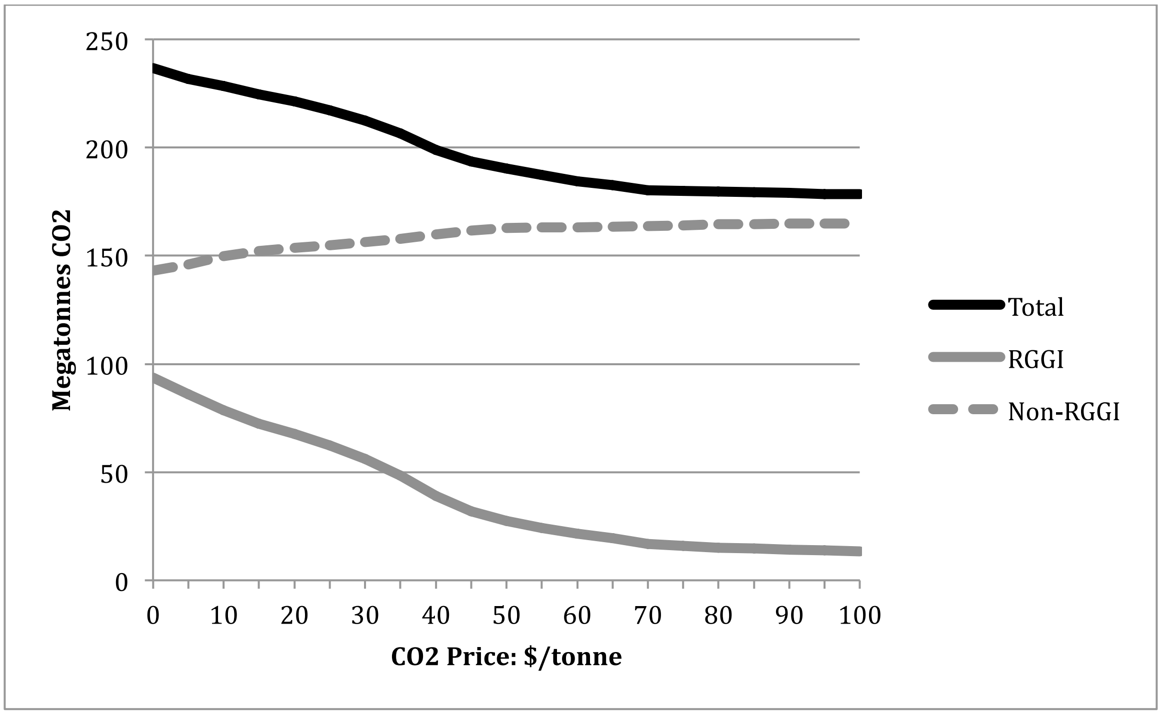

FIGURE 2.10: CO_2 Emissions from a range of RGGI CO_2 Prices in 2022

Figures 2.11 and 2.12 explain part of the reduced leakage. As in 2012, non-fossil fuel generators are omitted because there is no change in capacity or generation as CO_2 prices increase. Existing natural gas capacity is kept mostly intact, with about 11% (3 GW) of existing RGGI units decommissioned once prices get above \$80/tonne. Likewise, the 9 GW of coal capacity in RGGI is taken offline at CO_2 prices above \$70/tonne. For new natural gas plants, 12 GW is built regardless of CO_2 prices, half in RGGI and half outside of RGGI. As CO_2 prices increase, the total amount built increases, and the ratio shifts to include more new natural gas plants built outside of RGGI. At CO_2 prices of $100/tonne, over 16 GW of new natural gas capacity is built, almost 90% of that outside RGGI. Building more efficient newer plants in response to shutting down coal generation produces less leakage per plant than running older, less efficient more often, but more total leakage is present when investment is allowed.

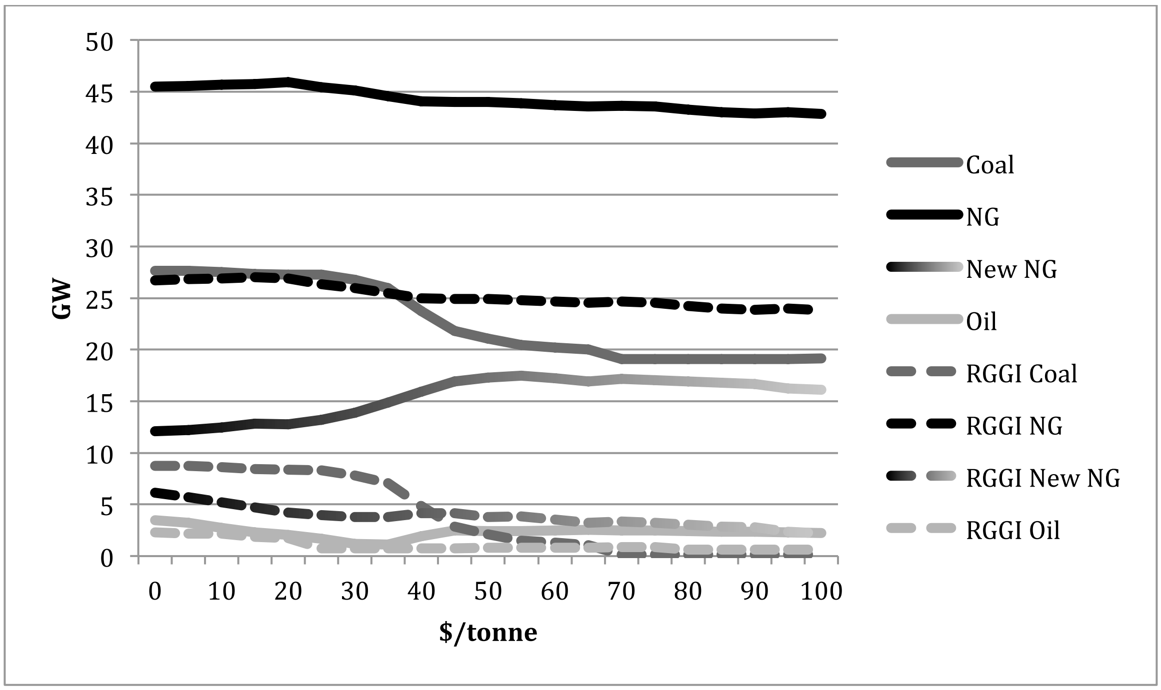

FIGURE 2.11: Fossil Fuel Capacity for a range of RGGI CO_2 prices in 2022

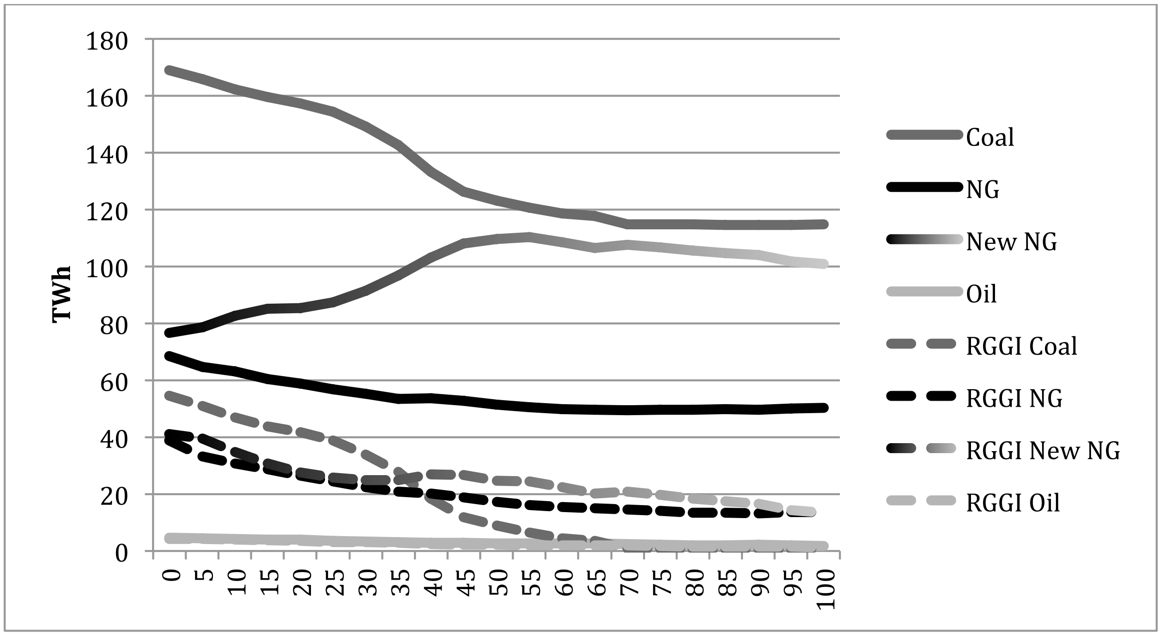

FIGURE 2.12: Fossil Fuel Generation for a range of RGGI CO_2 prices in 2022

Figure 2.13 summarizes the magnitude of carbon leakage as a result of regionally limited carbon prices in 2012 and 2022. The quantity charted is the total CO_2 increases in the non-RGGI units divided by the total CO_2 decreases from the RGGI units, or what percent of total RGGI CO_2 emissions non-covered units increasing output undo. Leakage is a greater concern at lower CO_2 prices – it reaches a maximum at \$5 or \$10/tonne in 2012 and 2022 respectively, then has a general downward trend as CO_2 prices increase. The spike in 2022 leakage from \$5-\$10/tonne is due to a number of factors. First, total CO_2 abatement by RGGI units at this stage is small – about 6% of total CO_2 emissions, so small changes have larger percentage effects. In general, RGGI units see a reduction in total generation of about 10 TWh for every \$5 increase in CO_2 prices at first, which quickly tapers off to 7-8 TWh/\$5 increase, and gradually decreases to about 1TWh/\$5 increase as prices approach \$100/tonne. Non-RGGI units generally increase their generation by about 5 TWh/\$5 increase in CO_2 prices, which tapers to a 1TWh/$5 increase as CO_2 prices increase past $50/tonne. However, as CO_2 prices increase from $5 to $10/tonne, the output of non-RGGI units increases by 10 TWh, mostly due to newly constructed natural gas plants. This is the largest increase in total generation and generation from new units in the sample, 50% above the next largest increase. It also reflects an increase in the average capacity factor of new natural gas units, from 68% at $0 and $5/tonne to 75% at $10/tonne.

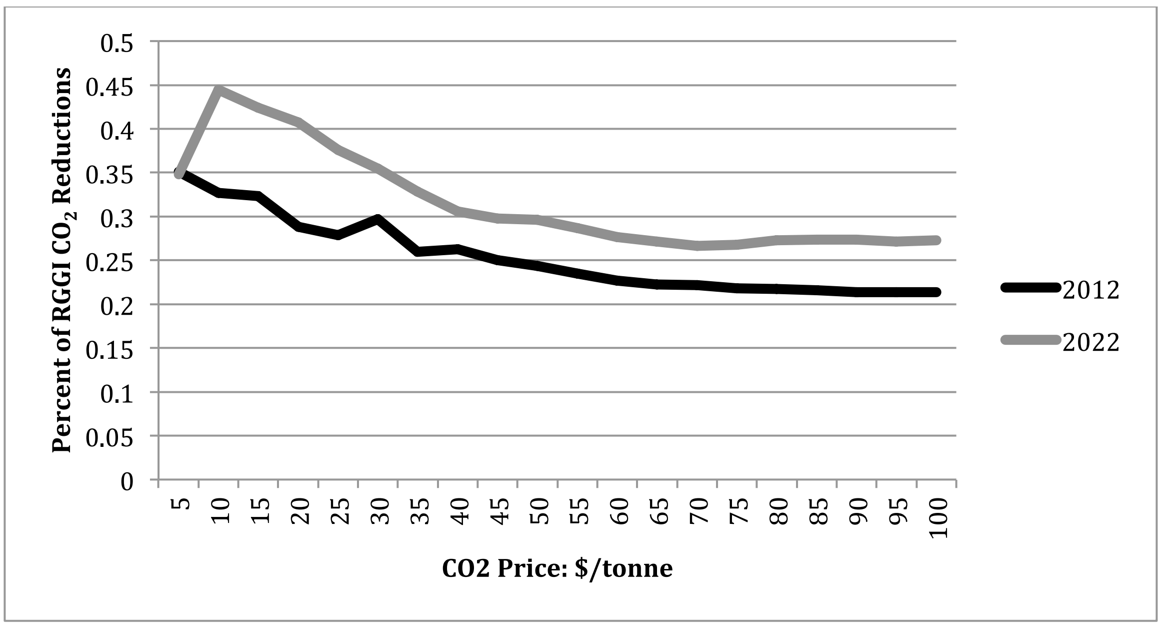

FIGURE 2.13: Leakage as a Percent of RGGI Carbon Reductions

Finally, to look at the effects of a unified emissions policy, the same analysis is repeated with a CO_2 price applied to every unit greater than 25 MW in the NPCC. Figures 2.14 and 2.15 compare this policy with RGGI. RGGI emissions are shown for each case as a comparison, though are not as important in the unified emissions price policy. First, note the unified policy is dramatically better at reducing total emissions. At high prices, total CO_2 emissions can fall to less than 40% of original levels, compared to 72% for RGGI-only emissions prices. The bulk of the units outside of RGGI are located in Pennsylvania, which relies heavily on coal generation, so there is more room for improvement when these units are included in addition to RGGI units.

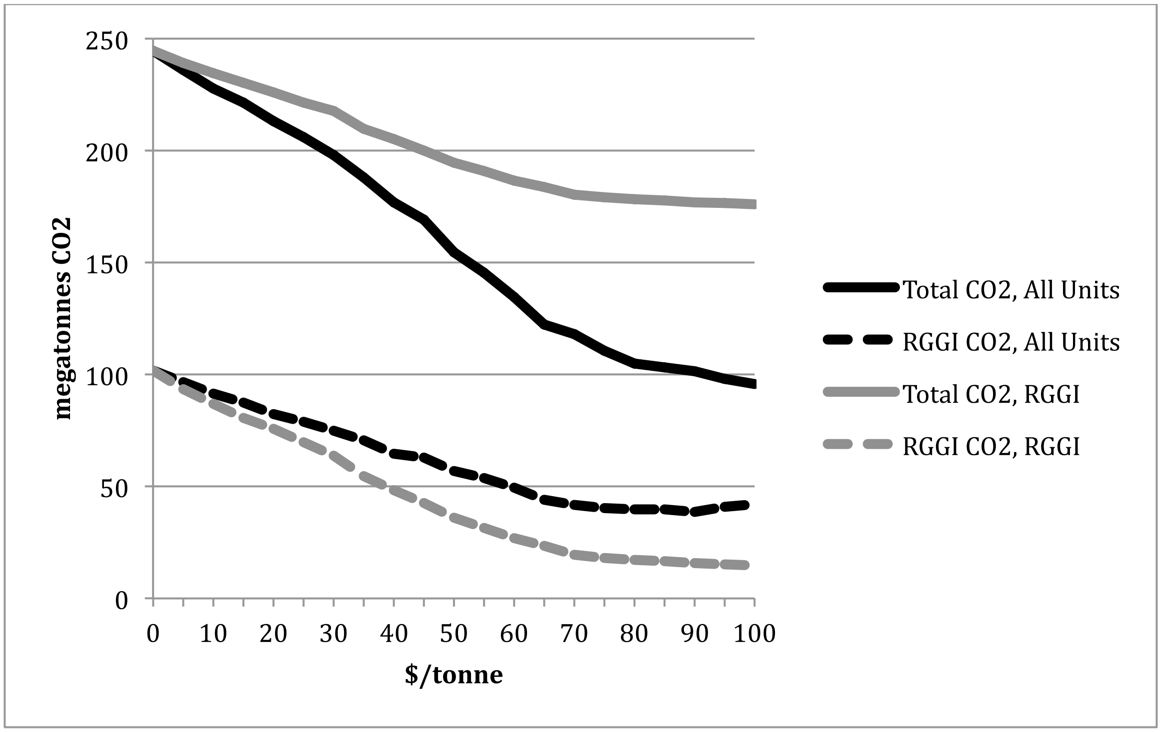

FIGURE 2.14: Comparison of CO_2 emissions versus CO_2 prices in 2012 for two emissions costs applications

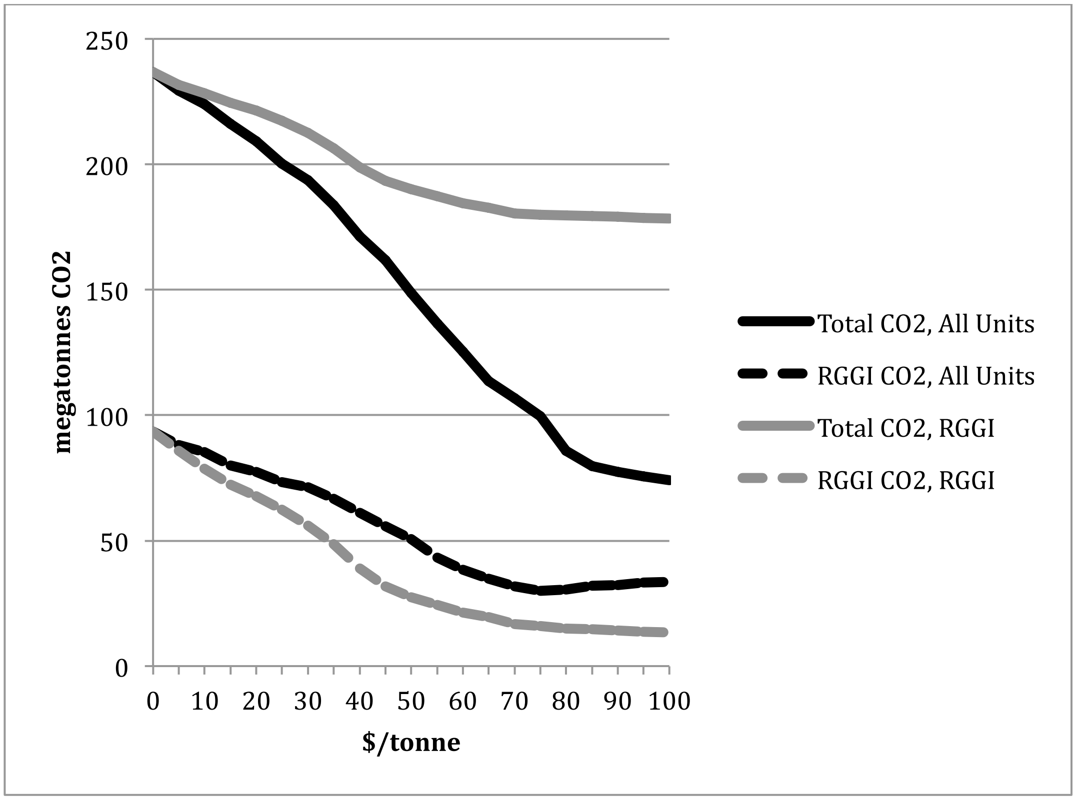

FIGURE 2.15: Comparison of CO_2 emissions versus CO_2 prices in 2022 for two emissions costs applications

Figures 2.16 and 2.17 confirm this hypothesis. As CO_2 prices increase and coal generation falls, the bulk of the reductions are not occurring in RGGI, especially in 2022. In 2012, 63% of the reduction in coal at CO_2 prices of $100/tonne occurs outside of RGGI, and in 2022, that increases to 67%. At the same time, at least half of new natural gas plants built are outside of RGGI. This proportion increases as the price of carbon increases. As with the rest of the charts of capacity and generation, there is no change in the non fossil fuel plants, and little change in the oil plants.

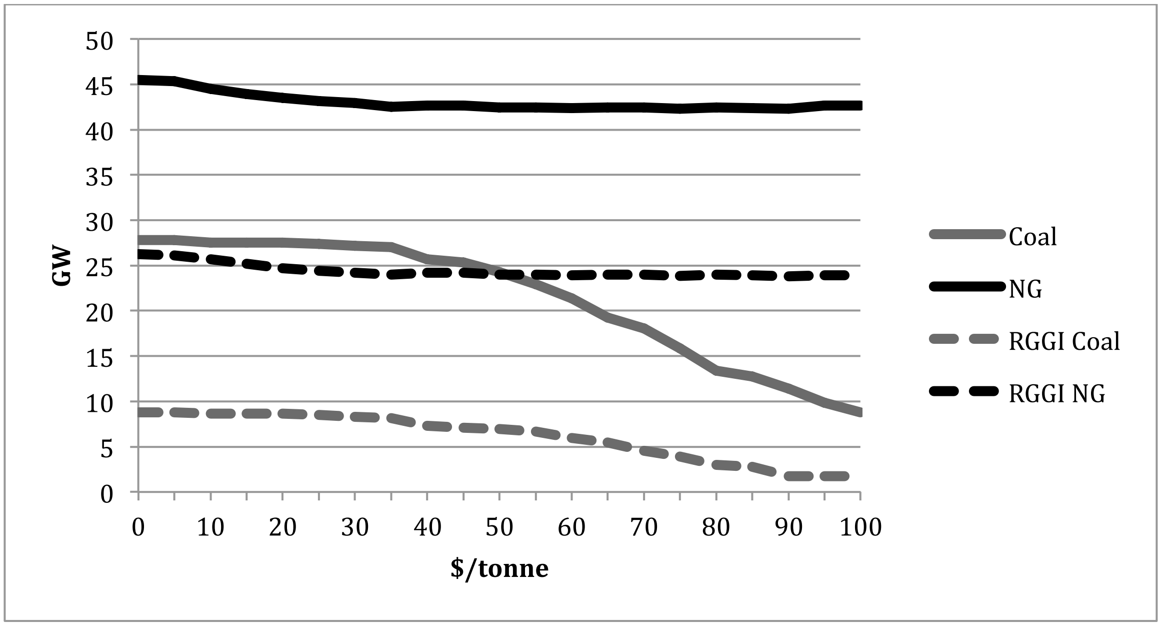

FIGURE 2.16: Coal and Natural Gas Capacity for a range of CO_2 prices with a unified emissions price policy in 2012

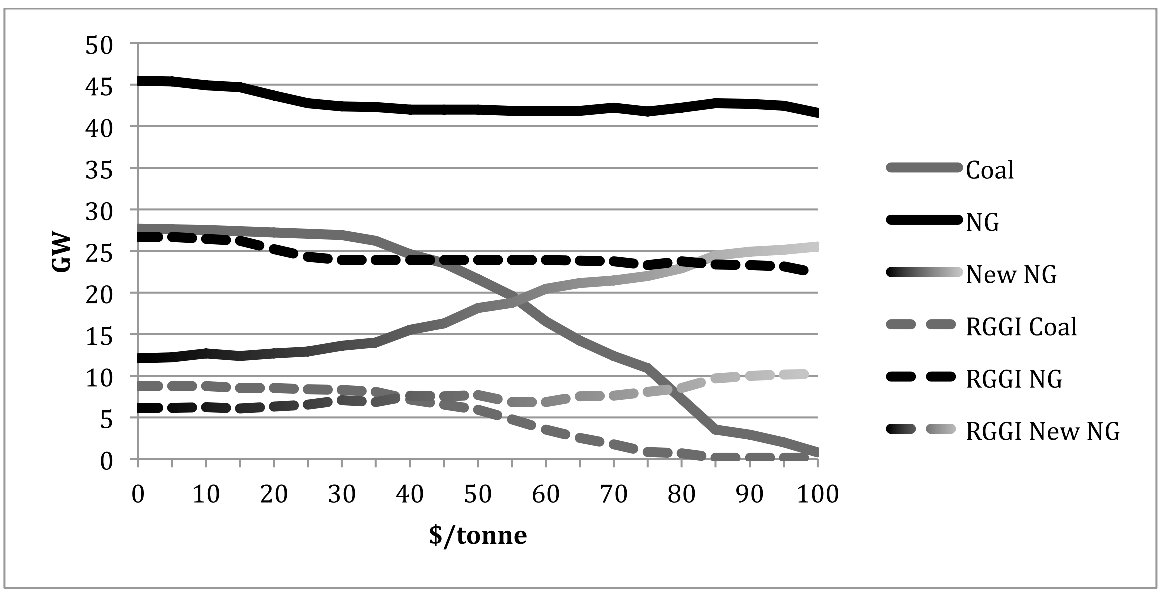

FIGURE 2.17: Coal and Natural Gas capacity for a range of CO_2 prices with a unified emissions price policy in 2022

IV. Online Contingent Valuation Survey

Earlier research (Ho et al, 2011) conducted an online contingent valuation survey regarding willingness to pay for carbon abatement. Survey respondents were drawn from The StudyResponse Project, a nationwide panel of 95,574 people. 520 panelists were invited to participate, and 420 completed surveys were received, for an 81% response rate. However, for this application, only the 79 respondents in the control group are used. The treatment group in the Ho et al study focused on examining the WTP of individuals depending on their relative culpability – the difference between their carbon footprint and a stated average. The control group was given no information about the difference between their carbon emissions. The actual contingent valuation question is shown in Figure 2.18. Although the contingent valuation question was stated with a constant marginal cost for abating carbon emissions, I assume that it is the extra cost per year people care about, not the actual levels of carbon emissions averted.

Green Energy

Suppose your electric utility were to offer you renewable energy appropriate to your area. For example, wind, solar, geothermal, or tidal power could all be offered, depending on your geographic location. Choose the option you would like to purchase from the table below. (Information from the Energy Information Administration of the Department of Energy.)

	Size of Block	Extra Cost per Month	Extra Cost per Year	Tons of CO2 Averted per Year
○	0 kilowatt hours	$0.00	$0.00	0 tons
○	50 kilowatt hours	$2.80	$33.60	0.405 tons
○	100 kilowatt hours	$5.60	$67.20	0.81 tons
○	200 kilowatt hours	$11.20	$134.40	1.62 tons
○	300 kilowatt hours	$16.80	$201.60	2.43 tons
○	400 kilowatt hours	$22.40	$268.80	3.24 tons
○	500 kilowatt hours	$28.00	$336.00	4.05 tons
○	600 kilowatt hours	$33.60	$403.20	4.86 tons

Submit

FIGURE 2.18: WTP question from online survey

Table 2.4 displays summary statistics for these individuals. Participants with any missing observations or who had obvious outlier answers to their carbon footprint questions were dropped. The variables included are CO_2 Total, a carbon footprint estimated from information provided in the survey; NEP, a measure of environmental attitudes, from the New Ecological Paradigm (Dunlap et al 2000) to create a 55-point variable from 10 5-point Likert scale questions; politics, a binary variable for self-reported political status; children, a binary for the presence of children in the household; gender, a binary for gender; age; income: household income in levels; Education, a binary for education status; and Democrat, a binary for party affiliation.

TABLE 2.4: Summary information for participants in sample

	Mean
WTP (Lower bound)	143.33 (15.41)
CO_2 Total	23.3 (2.35)
NEP	34.01 (0.81)
Politics	0.75 (0.05)
Children	0.58 (0.06)
Gender	0.57 (0.06)
Age	37.61 (1.17)
Income	5.04 (0.23)
Education	0.53 (0.06)
Democrat	0.41 (0.06)
N=	79

Standard errors in parentheses

Because the payment card response items are discrete and ordered, Cameron and Huppert's (1989) interval modeling format extension is used. This model assumes that selecting a particular threshold value provides the lower bound of a willingness to pay (WTP) interval, which is bounded by above by the next cost point. The highest interval is an exception to this rule, since there is no stated upper bound. The upper bound for the highest interval was assumed to be \$1,000/year. Assuming a logistically distributed WTP function yields the following log likelihood function, equation (5):

$$Ln(L) = \sum_{i=1} ln[F(\frac{\gamma Z_i - t_{iU}}{\theta}) - F(\frac{\gamma Z_i - t_{iL}}{\theta})] \qquad (5)$$

F(.) indicates the logistic distribution, Z is a vector of covariates, t_{iU} is the upper bound of the interval selected, t_{iL} is the lower bound of the interval selected, and the scale parameter $\theta = \sigma \sqrt{3}/\pi$. E(WTP) = γZ and var(WTP) = σ^2. Table 2.5 shows the results of this maximum likelihood estimation. NEP is the explanatory variable with the most predictive power, which is unsurprising. People who have stronger feelings about the environment want to voluntarily spend more to abate carbon. Education, being liberal, having children, and age are also positively correlated with a greater willingness to pay.

This estimation was then used to estimate median WTP for carbon abatement instead of a lower bound of WTP for carbon abatement. This information is then used to calculate a distribution of willingness to pay for carbon abatement, depicted in Figure 2.19. The maximum WTP is \$337.09, and 50% of the sample would be willing to pay at least \$165/year for carbon abatement.

TABLE 2.5: MLE Results for Contingent Valuation Experiment

Variable	Coefficient
Constant	-127.41 (113.61)
CO2 Footprint	0.58 (0.88)
NEP	7.41*** (2.49)
Politics	5.98 (38.02)
Children	9.25 (35.85)
Gender	-23.46 (36.05)
Age	0.42 (1.75)
Income	-2.82 (8.56)
Education	48.17 (35.55)
Theta	80.46*** (8.30)
Observations	79
Log Likelihood	-176.44

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
All samples exclude outliers and observations with any missing values

V. A Model of Public Acceptance for Bi-Regional and Unified Carbon Markets

With the information from the previous two sections, a model for acceptance of bi-regional and unified carbon policies can now be constructed. Section three gives us information about the relative costs of reducing CO_2 emissions under the two policy regimes, while section four gives us information about willingness to pay for CO_2 abatement.

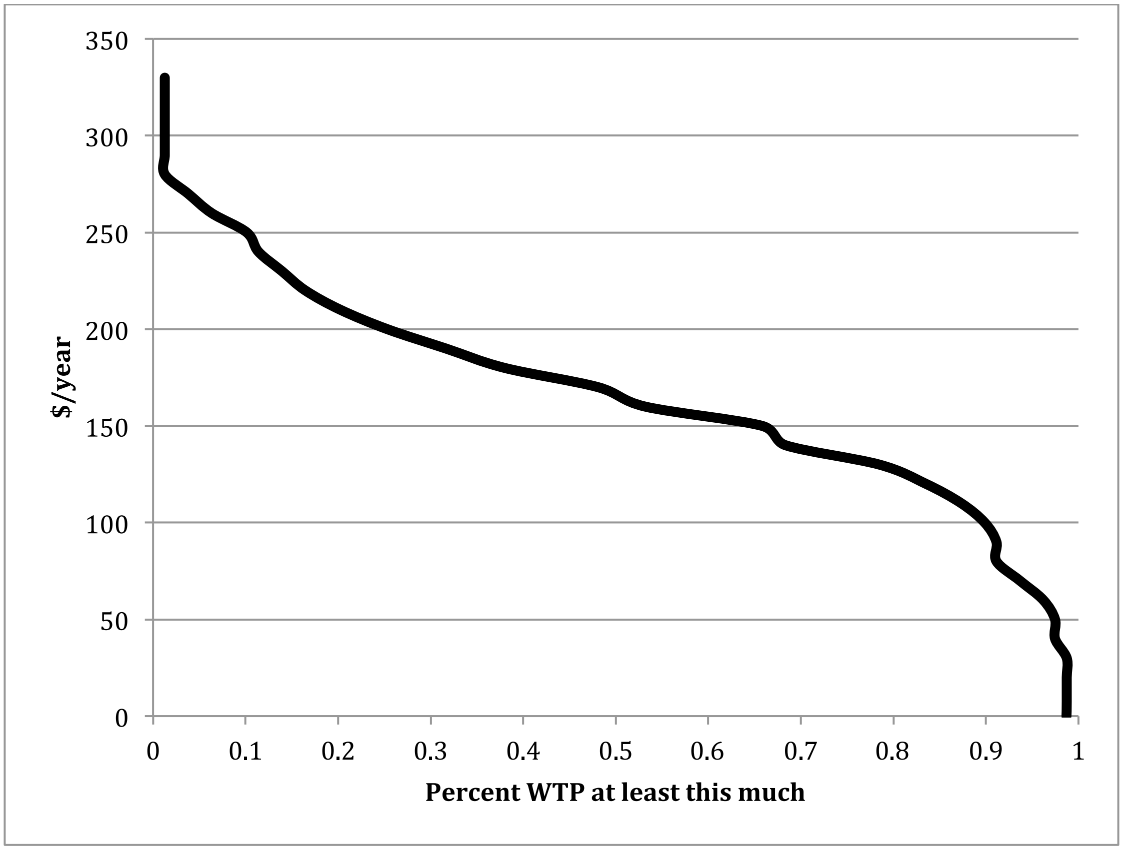

FIGURE 2.19: Distribution of WTP for carbon abatement

First, to analyze of the effects of reducing CO_2, regressions were run, regressing total CO_2 emissions, RGGI CO_2 emissions, or total wholesale prices on carbon emissions price and carbon emissions price squared. The results from these regressions are shown in Tables 7 and 8. These regressions fit the data very well with R^2 of 0.96 or greater.

With the information about WTP for carbon abatement, and the information about carbon emissions and prices in the NPCC, it is possible to calculate the maximum abatement under each price regime that a majority of the population would be willing to support, as well as what percentage of the population would be willing to pay for various carbon abatement policies. According to the Energy Information

Administration, residential sales of electricity in 2010 were 1,450,759 million kWh (2011.) At the same time, there were 112,611,029 households in the United States (Census, 2010). This gives an average household consumption of 12,882 kWh/household/year.

Given a CO_2 price, CO_2 emissions and LMP can be calculated using the regression results in Tables 2.6 and 2.7. Or, given a CO_2 emissions target, the necessary CO_2 price can be calculated, and from that, wholesale prices can be calculated. With the new wholesale price, demand response can be calculated using the same -1 elasticity as in the SuperOPF. Finally, with prices and consumption, total electricity expenditures can be calculated. The sum of electricity expenditures and the value of lost load is compared with the original electricity expenditures (or expected electricity expenditures in 2022) at $0/tonne CO_2 prices to calculate the additional cost per household of various CO_2 emissions prices.

TABLE 2.6: Summary Results from Regressions of Total CO_2 Output for various Emissions price applications in 2012 and 2022

CO_2 Price Application	All	RGGI	All	RGGI
Year	2012	2012	2022	2022
Constant	251.902***	248.038***	244.952***	240.957***
	(3.581)	(1.397)	(3.880)	(1.613)
CO_2 Price	-2.226***	-1.347***	-2.042***	-1.302***
	(0.166)	(0.065)	(0.180)	(0.075)
CO_2 Price^2	0.006***	0.006***	0.002	0.007***
	(0.002)	(0.001)	(0.002)	(0.001)
R^2	0.9864	0.9902	0.9871	0.9829

Standard Errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Three sets of results are presented in Table 2.8: a 10% CO_2 reduction (the RGGI goal), a 17% CO_2 reduction (the goal of the proposed Kerry-Lieberman and Waxman-Markey Bills) and a reduction that 50% of people would be willing to pay for. In the first two cases, the unified policy is cheaper per affected individual and results in lower CO_2 prices than the RGGI policy. In the third case, all the costs are equal, and the unified cases have lower CO_2 emissions, although CO_2 prices are lower for the RGGI 2022 case. Of course, the unified policy has a CO_2 price applied to every unit in the NPCC, and more people are affected by the policy, so the extra cost per year is paid by more people. But even if CO_2 prices are charged only to generators in RGGI, the costs of electricity increase, even for those individuals not in a RGGI state. This is because the marginal generating units become more expensive, whether because more expensive units are brought online in the non-RGGI region, or because the marginal units in RGGI are now charged for their CO_2 emissions. Also, policies are less expensive in 2022, as the addition of new generating units can lower the cost of compliance. From the 10% and 17% goal cases, it is clear that any of the effective policies to limit CO_2 emissions would not be approved if willingness to pay were the only criteria on which voters acted. The last case shows what level of policies would be acceptable to the public: a 1-3% reduction in the near term and a 6-7% reduction in the medium term. Over the long run, additional investment in new, efficient capacity might be expected to increase the amount of CO_2 people would voluntarily choose to abate. New types of power plants, such as carbon capture and storage plants might change these conclusions as well.

TABLE 2.7: Summary Results from Regressions of Total and RGGI Average LMP for various Emissions price applications in 2012 and 2022.

Region	All	All	RGGI	RGGI
Year	2012	2022	2012	2022
	70.361***	71.635***	70.856***	72.778***
Constant	(0.190)	(0.089)	(0.287)	(0.041)
	0.313***	0.317***	0.365***	0.183***
CO2 Price	(0.009)	(0.004)	(0.013)	(0.002)
CO2	0.002***	0.0004***	-0.001***	0.0002***
$Price^2$	(0.0001)	(0.00004)	(0.0001)	(0.00002)
R^2	0.9997	0.9998	0.9998	0.9963

Standard Errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 2.8: Summary Results from Three Carbon Abatement Cases

10% Reduction								
Model	Year	CO_2 Price	CO_2 Emissions	LMP	Load	Extra Cost per Year	Carbon Abatement	Percent Support
Unified	2012	$14.85	220	$75.45	96.11%	$337.47	10%	0.00%
Unified	2022	$12.29	220	$75.53	96.05%	$238.04	10%	12.65%
RGGI	2012	$21.84	220	$78.35	94.04%	$505.72	10%	0.00%
RGGI	2022	$17.64	220	$76.01	95.71%	$266.22	10%	5.06%
17% Reduction								
Model	Year	CO_2 Price	CO_2 Emissions	LMP	Load	Extra Cost per Year	Carbon Abatement	Percent Support
Unified	2012	$23.43	203	$78.79	93.72%	$530.77	17%	0.00%
Unified	2022	$20.96	203	$78.28	94.09%	$397.65	17%	0.00%
RGGI	2012	$39.23	203	$83.63	90.26%	$792.69	17%	0.00%
RGGI	2022	$36.15	203	$79.39	93.29%	$460.41	17%	0.00%
50% Approval Reduction								
Model	Year	CO_2 Price	CO_2 Emissions	LMP	Load	Extra Cost per Year	Carbon Abatement	Percent Support
Unified	2012	$6.88	237	$72.61	98.14%	$165.00	3.17%	50.63%
Unified	2022	$8.44	228	$74.31	96.92%	$165.00	6.85%	50.63%
RGGI	2012	$4.87	242	$72.61	98.14%	$165.00	1.12%	50.63%
RGGI	2022	$8.37	231	$74.31	96.92%	$165.00	5.76%	50.63%

VI. Conclusions

Using a transmission-constrained model with actual generator data is essential for estimating impacts to the electric grid from large-scale policies. Transmission and generation constraints are a factor for all of the analyses in this paper, and provide a more realistic picture of the effects of policies than the "bubbles and pipes" models commonly used which neglect intra-region transmission constraints and greatly simplify inter-region transmission.

Under bi-regional emissions policies, leakage is a real concern. With no investment in new capacity, 21-35% of carbon reductions are undone by increased emissions in the non-covered area. After time for new investment, the situation is even worse, with at least 25% of carbon reductions undone by increased emissions. Relative levels of leakage are higher at low carbon prices, as generation and transmission constraints limit how much electricity can be imported, especially in already-congested areas. Additionally, bi-regional policies make it more expensive to achieve emissions reductions of equal magnitude when compared to unified emissions regimes, making it more unlikely that they will be politically viable. Assuming that all states have homogenous voter attitudes about climate change. Some voters are more environmentally concerned and willing to take on greater costs for themselves in exchange for some emissions reductions.

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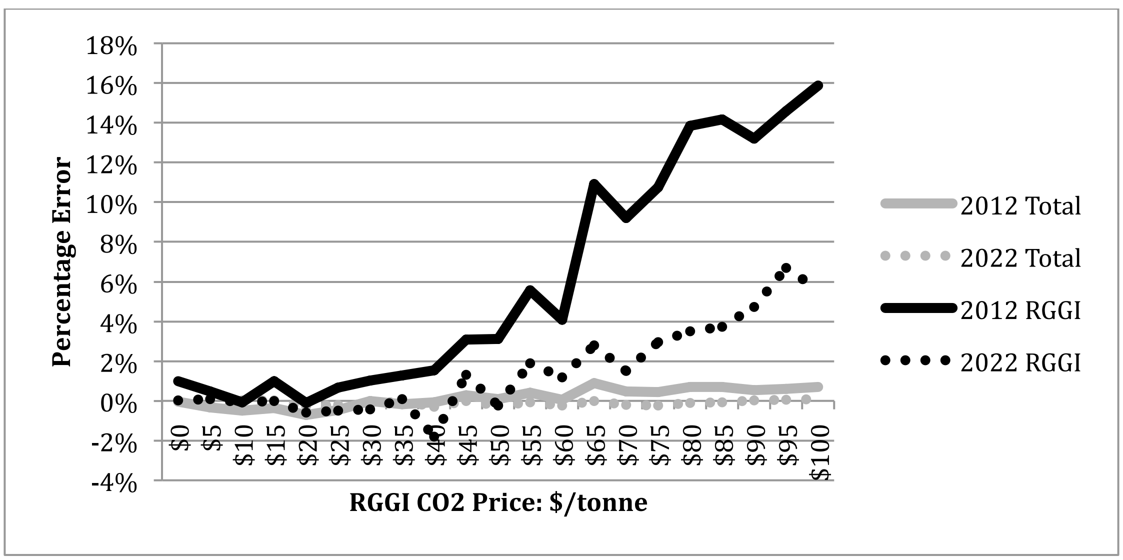
APPENDIX

In order to examine whether the increased computational complexity required by this reduced network model is justified by differences in results, this Appendix compares the results of the reduced network model to a bubbles and pipes model of the same network. In the bubbles and pipes model, the 36 nodes are split into six bubbles: Ontario, Hydro-Quebec, New Brunswick, New York ISO, ISO New England and PJM. In Figure 2.3, the Ontario region is the box labeled IMO in the upper left hand corner, which consists of 5 busses, 80001-81615. The PJM region is in the lower left hand corner and represented by busses 1 and 5028. The NYISO is the middle and bottom right corner, represented by 19 busses, from 74316 to 79800. ISO New England is in the middle right side, represented by eight busses, 70002-73663. Hydro-Quebec and New Brunswick are represented by one bus each, 84819 and 87004 respectively and in the upper right corner. Transmission constraints between the regions are modeled with a single "pipe" that represents the sum of all flow constraints between the regions, while transmission constrains within each region are ignored.

Appendix Figure 1 summarizes the differences in predicted CO_2 output (both total CO_2 and RGGI CO_2) for a range of RGGI prices between this network model and the bubbles and pipes model. The amount of total CO_2 emissions predicted by each model is very similar, with only an average difference of 0.16% in 2012 and -0.09% in 2022, with a maximum deviation of 0.89%. However, the amount of CO_2 emissions in the RGGI states vary greatly between the two models. In 2012, the average deviation is 5.96%, but the maximum deviation is 15.87%. As the CO_2 prices in RGGI increase, the deviations between the models do as well. This is consistent with earlier results that showed that intrazonal transmission constraints are the binding constraint when examining leakage, not interzonal transmission constraints. In the case of RGGI emissions, it is often the transmission lines within New York state that limit the amount of generation that can moved to uncovered busses in Canada or PJM. Because it lacks these intrazonal constraints, the bubbles and pipes model predicts an unrealistically high level of leakage (ie, more generation moving from RGGI to outside of RGGI) when compared to the reduced network model.

For analysis of policies that only result in minor changes from the real world, simpler models such as a bubbles and pipes framework provide an adequate modeling tool. However, the further a system diverges from initial conditions, the more important better, more detailed models become.



APPENDIX FIGURE 1: Differences in CO_2 Emissions between Network and Bubbles and Pipes Model for a range of CO_2 Prices

CHAPTER 3

RELATIVE CULPABILITY IN CONTINGENT VALUATION AND LABORATORY EXPERIMENT OF WILLINGNESS TO PAY TO REDUCE NEGATIVE EXTERNALITIES

Benjamin Ho[11], John Taber[12], Greg Poe[13], and Antonio Bento[14]

ABSTRACT

Recent large-scale field experiments have shown that peer information nudges can have significant effects on behavior, inducing people to reduce their production of negative externalities. Related work in psychology demonstrates that inducing feelings of personal culpability by showing people information about their peers can induce pro-social behavior. This study uses a contingent valuation experiment and a parallel lab experiment to further explore patterns of responses that have been suggested in the emerging literature on norm-based environmental interventions The field–level finding of asymmetric responses between those whose environmental or group impacts are above or below the norm is found to be robust across decision settings. However, substantial heterogeneity in responses to peer information is observed across a number of demographic and other respondent–specific dimensions not able to be

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explored in large scale field experiments, raising questions about the universality of peer-information effects and the design of such programs.

I. Introduction

Recent large-scale field experiments demonstrate that peer comparisons and social-norm nudges are effective tools for inducing the conservation of privately purchased goods that collectively create negative public externalities. Randomized residential electricity experiments that have monitored energy use and informed households of their personal consumption levels relative to a neighborhood norm provide evidence that energy consumers significantly reduce their energy consumption relative to a control group that does not receive such comparative information (Ayers et al. 2009; Allcott and Mullainathan, 2010; Costa and Kahn, 2010; Allcott, 2011). Such behavioral change-based interventions, as opposed to more traditional price instruments, can indeed be powerful, especially amongst specific groups of the population. Ferraro and Price (2011), for example, study the effects of providing non-price interventions for household water use and find that, in the short run at least, the social-comparison effect is equivalent to that which would be expected if average prices were to increase by 12 to 15 percent; in a study of residential electricity consumption, Ayers et al. (2009) estimate that non-price, peer comparison intervention induce the equivalent consumption response as a 17 to 29 percent price increase.

While the average treatment effect has been shown to be significant, it is apparent that there is variation in response patterns to norm-based interventions. Notably, in a localized study of 290 households, Schultz et al. (2007) demonstrate that social-norm nudges may create a "boomerang effect" in the sense that below average consumption households may actually increase their energy consumption when they are informed that their baseline consumption is below the average of their peer group. In this same study, high-energy users significantly decreased their electricity consumption levels relative to the baseline, as expected from the focus theory of normative behavior (Cialdini et al., 1991). This asymmetry in treatment effects has been replicated, to an extent, in large-scale field experiments with observations ranging from 75,000 to 600,000 households. However, rather than observing a strong boomerang effect that increases consumption, there more commonly seems to be a zero, or muted negative, effect on consumption patterns of low-use households. Allcott (2011) estimates that social-norm treatment effects are not significantly different from zero for the lowest three deciles of baseline electricity users, but that there is a significant mean treatment effect in high-use households ranging from about -3.7% for the 8th decile to over -7% in the 10th decile. Ayers et al. (2009) similarly find no significant treatment effect on two out of lowest three deciles of baseline electricity use (the second decile had a significant treatment effect of approximately +1%), while consumption levels significantly decline by about -3% to -7% for the top three baseline energy deciles. In a regression framework, Ferraro and Price (2011) estimate that the "social norm effect for our high user group is approximately 94.1 percent greater (5.28 versus 2.72 percent relative reduction) than for our low user group – a difference that is significant at the p<0.005 level." In all, while strong boomerang effects may not be evident, there does appear to be an important asymmetry in responses to social-norm interventions between households with above and below norm consumption levels.

Moreover, although responsiveness to norm-based messages have been demonstrated in a number of domains (e.g. Frey and Meier, 2004; Cialdini et al., 2006; Salganik, Dodds, and Watts, 2006; Cai, Chen, and Fang, 2009) recent research in the energy-social norms literature suggests that non-pecuniary effects may not be as universal as previously thought. Different socio-economic groups may have heterogeneous responsiveness to peer information. In interpreting these results, Costa and Kahn (2010) argue that:

> "behavioral economists have underestimated the role that ideological heterogeneity plays in determining the effectiveness of energy conservation "nudges"… we find that liberals and environmentalists are more responsive to these nudges than the average person. In contrast, for certain subsets of Republican Registered voters, we find that the specific "treatment nudge" that we evaluate has the unintended consequence of increasing electricity consumption." (p. 2)

In this paper we show that such asymmetric and heterogeneous responsiveness is also manifested in contingent valuation and laboratory economics experiments in which we can control the normative information that the subject receives. Along the lines of Bateman et al. (2008), who demonstrated parallelism between contingent valuation responses and "inconsistencies…found in everyday decisions involving real commitments" (p. 125), we argue that evidence of convergent behaviors across methods lends validity to each. Further, the survey application allows us to explore whether heterogeneity in response patterns occurs in demographic and other respondent-specific dimensions not able to be explored in large-scale field tests. The laboratory experiment permits exogenous control of the individual's impact, avoiding possible endogeneity effects that may arise in field and contingent valuation studies.

The contingent valuation study calculates the carbon footprint of a nationally representative sample of consumers by asking questions about their energy-related consumption habits. A carbon footprint is defined to be the number of tons of carbon dioxide emissions an individual is personally responsible for based upon his or her energy consumption decisions in a given year. We then provide subjects in the treatment group information about how their carbon footprint compares to those of others in the study and elicit willingness to purchase green electricity to induce a feeling of relative culpability. In an effort to parallel the field contingent valuation study, the laboratory experiment has student subjects purchase "private commodities" (analogous to electricity) that generate a negative externality (analogous to pollution) for a group in which they are a member. A treatment group is given information about the private, pollution generating choices of others and the subjects are subsequently given an opportunity to contribute to a fund that would reduce the negative harm created by the externality. In the taxonomy of Harrison and List (2004) we present results from a framed field experiment coupled with a conventional laboratory experiment.

Beyond demonstrating convergent validity between field experiments, economic laboratory exercises, and contingent valuation responses and identifying further dimension of response heterogeneity to social- norm nudges, our research contributes to the broader literature on norm-based conservation incentives. First, in contrast to energy and water conservation in which the psychological cues and economics savings are mutually reinforcing, our contingent valuation study of willingness to pay for “green electricity” and laboratory experiment study of willingness to contribute to a public good involve tradeoffs between private costs and societal or group gains. As such, our work extends the work of Shang and Crosson, (2009) and Chen (2009) who show that some individuals are willing to bear additional monetary burdens in response to information about social norms. Second, much of the previous research on norm-based messaging has been confined to providing information about peer consumption in the domain of the desired conservation activity. For example, studies that seek to encourage towel re-use in hotels, provide information about towel re-use habits of others (Goldstein et al. 2008). At the same time some limited research suggests that social-norm information in one domain of decision-making affects decisions in other domains (Mazar and Zhong, 2010; Keizer et al., 2008). These studies have considered moral licensing—learning you are more more moral in one domain makes you less moral in another—and moral cleansing—learning you are less moral in one domain makes you more moral in another. Our research speaks to both and finds an asymmetric response. This asymmetry could produce a “moral rebound” effect that limits the effectiveness of social-norm based policy interventions. Therefore, understanding such response patterns could significantly improve the design of interventions and explain the limited effectiveness of past trials. More mundanely, our design speaks directly to the effect of carbon footprint calculators on the demand for carbon offsets and green electricity.

Our main findings are that information about the behaviors of others influences public provision behavior in contingent valuation and lab experiments. The effect of social information is *asymmetrical*— the moral cleansing effect for individuals above the norm is larger than the moral licensing effect for those whose consumption and negative externality effects are below the perceived norm. Finally, we demonstrate that systematic heterogeneity in responses to social norm nudges extends substantially beyond the political/environmental dimensions explored in Costa and Kahn's field experiment. As we argue in the concluding section, these findings, in conjunction with emerging field research, raise questions about the universal efficacy of nudges vis-à-vis pricing incentives.

The remainder of this paper is organized as follows. In the following section we review previous economic and psychological conceptualizations of the notion of culpability or guilt in choice and valuation and how these concepts have been tested in laboratory and contingent valuation exercises. We then provide details on our experimental design and data. In the fourth section we provide empirical analyses of our experimental results with respect to asymmetry in response patterns above versus below norm respondents. The fifth section lends supporting evidence to the Costa and Kahn results, and expands the analysis of heterogeneity to demographic and respondent-specific characteristics available from survey data. Conclusions and discussion are provided in the final section.

II. Background on Culpability

In this research we explore how willingness to pay to prevent a public bad is affected by an individual's relative culpability, which we define to be the amount of social damage resulting from an individual's actions relative to damages cause by others.[15] Whereas the mechanisms that might induce conformity to a perceived social norm have been extensively studied in economics (see for example Bikhchandani, Hirshleifer, and Welch, 1992; Ellison and Fudenberg, 1993; Bernheim, 1994; Akerlof and Kranton, 2000; Glaeser and Scheinkman, 2003), the mechanism of culpability has received less attention. Guilt has been explored in the psychology literature (see Baumeister, Stillwell, and Heatherton, 1994 for a review). Perhaps most famously, Carlsmith and Gross (1969) induced guilt in subjects by having them administer electric shocks to another person, a confederate. Later, when subjects believe they have completed the experiment, they are asked to donate blood. Subjects who actually administered the shock are much more likely to agree to donate, relative to subjects who merely observed the shocking.

Building from psychological foundations and psychological game theory (see Geanakoplos, Pearce, and Stacchetti (1989), Charness, Dufwenberg and co-authors construct a general theory of guilt aversion in which decision-makers experience guilt if they believe they let others down (e.g. Dufwenberg and Lundhom, 2001; Charness and Dufwenberg, 2006, 2007; Battigali and Dufwenberg (2007)). With supportive results from "Trust Game" experiments, they propose that this general theoretical framework can be extended to specific instances, such as public goods games and social norms, where it seems plausible that decision-makers are affected by guilt. In doing so these authors take care to distinguish the role of guilt aversion from conformity: "A norm is a social moral expectation a definition of which acts people in

[15] Our focus is on relative culpability because pilot experiments found that information about one's absolute level of social damage without comparison to one's peers had no effect on behavior.

society will judge as right or wrong...Too many authors use "norm" just to mean ``conformity in behavior''. (Dufwenberg and Lundhom, 2001, p. 510).

Andreoni's (1995) prior research on public goods suggests that such motivations may depend on whether the provision of the public good is framed positively or negatively. In Andreoni (1995), two groups of subjects participated in strategically identical public goods provision games, but with two separate framings. In one, the experiment was framed as providing a public good so that subjects would be motivated by warm glow altruism; in the other, the experiment was framed as avoiding a public bad, so that subjects would be motivated by a desire to avoid a "cold prickle" of guilt. Sonnemanns et al. (1998) conduct a like set of experiments in a threshold provision setting, alternatively framing the experiments as provision to provide a public good and prevention of a public bad. In both the Andreoni and Sonnemanns et al. studies, the tendency to free ride was more prevalent in the negative framing. Similarly, Solnick and Hemenway (2005) present informal survey evidence where positional concerns matter more for public goods rather than for public bads.

In the specific area of environmental norms, Bamberg and Moser (2006) conduct a meta-analysis of the literature on psychological mechanisms that promote pro-environmental behavior, finding that both social norms and guilt are important correlates to pro-environmental attitudes and behavior. Clark, Kotchen and Moore (2003) find that participation in a green electricity program is correlated with self-reported altruism and pro-environmental attitudes as measured by the New Environmental Paradigm (NEP). Brouwer et al. (2008) test the "passenger pays principle" to find that air travelers' perceived responsibility for climate change, awareness of the environmental impact of flying, and the frequency of flying were all positively correlated with WTP for a per-flight carbon offset program. This notion of personal responsibility in creating public harm is an extension of what Kahneman (1993) refers to as an "outrage effect", in which people are willing to pay more to avoid an environmental problem if they think it is human-caused than if they think that it is an outcome of nature (Bulte et al., 2005). Kahneman (1993) and Brown et al. (2002), amongst others have demonstrated this "outrage effect" on contingent valuation responses.

Our experiments complement the aforementioned literature by honing in on the individual culpability in contingent valuation and public goods experimental settings. We use peer information to manipulate the norm in a sequential setting most similar to the framing experiments of Andreoni (1995) and Sonnemans et al. (1998). Rather than split "Provision of Public Good" and "Prevention of Public Bad" samples as done in these studies, however, we employ a sequential framework: in the first stage of the experiment, we observe private decisions in a negative externality setting; the second stage involves a public goods contributions game in which contributions mitigate the negative effects of decisions in the first stage. We expect two main outcomes. For those who learn they contribute more to the negative externality than the perceived norm, i.e. have positive relative culpability, we expect they will be more altruistic in the second. For those who experience negative culpability, by learning they contribute less to the negative externality than the perceived norm in the first stage, we expect they will be less altruistic in the second. We find support for both of these effects, but we find that the former dominates. All treatment groups behaved less altruistically than those who received no information at all. This “moral licensing” effect has been explored by Mazur and Zhong (2010) who find that those who are given the opportunity to purchase green goods are more likely to cheat on an exam. Similarly, in one field experimental test of the “broken windows” effect, Keizer et al. (2008) find that observing others violate one social norm makes subjects more likely to violate other social norms. Our results further demonstrate that the effect predominates in those pre-disposed to provide more public goods in the second domain—for example Democrats, replicating in a lab and contingent valuation context the findings of Costa and Kahn (2010) who observed that the affect is limited to Democrats in a field experiment on electricity conservation. We extend their work to show that the heterogeneous effect exists along other dimensions as well.

III. Experimental Design

Contingent Valuation Experiment:

The broad objective of the contingent valuation survey was to gather information from participants that allowed us to calculate a carbon footprint for each respondent and then elicit their willingness to pay for a green electricity program given information about their own carbon footprint and, in some treatments, their carbon footprint relative to those of another survey participant. Participants for the online hypothetical survey were recruited through The StudyResponse Project, a nationwide panel of 95,574 people. The diversity of the sample, as seen in the summary statistics in Table 1 will be important for our analysis. Participants were chosen at random and emailed the URL for the survey. For completing the survey, participants received $5. 520 panelists were invited to participate, and we received 420 completed surveys for an 81% response rate.

There were four steps in the survey: I) Eliciting demographic questions to calculate the subject's carbon footprint; II) Providing information about International Panel on Climate Change (IPCC) predictions on the impacts of climate change; III) Showing subjects their estimated annual carbon footprint based on the input they provided; and IV) Eliciting individual demand for green electricity. For the control treatment, subjects were not provided any information about the carbon footprint of others. All other subjects received information about the carbon footprint of "Others like you who took this survey". (See Figure 3.1)

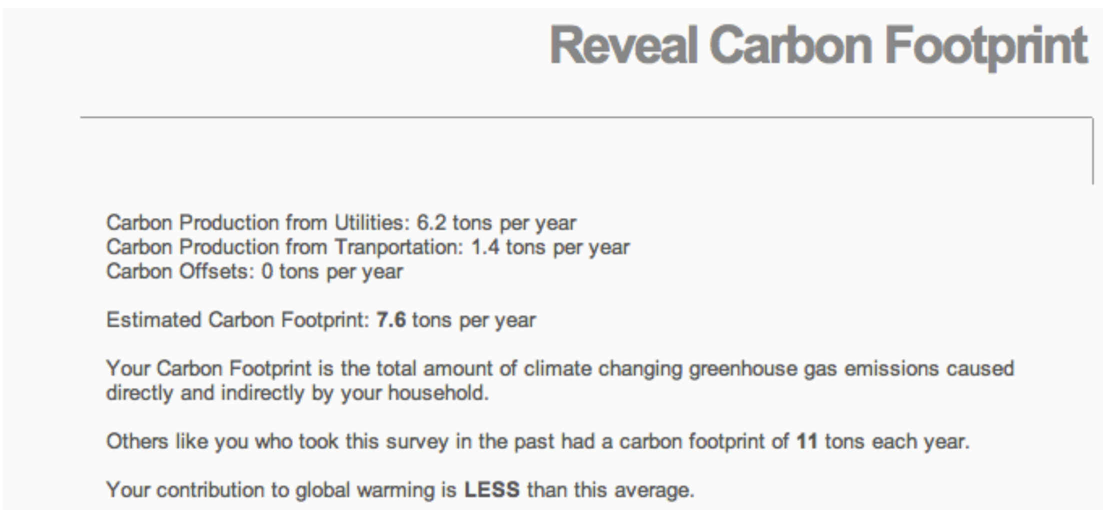

FIGURE 3.1: Information about Carbon Footprint presented in the survey. The "low treatment" (11 tons) is shown.

Part I of the survey consisted of several web pages eliciting information about energy use, including housing characteristics (type, age, size of residence, and location), home energy use (monthly electric and gas bill expenditures, type of fuel used to heat house, whether the household generates or purchases electricity);

automobiles (number, models, use of each vehicle) and transportation choices (use of public transportation, frequency of short and long domestic flights, frequency of international flights). Subjects were also asked about whether they purchased carbon offsets and if so, how many had they purchased. Only 31 subjects reported having purchased carbon offsets.

Subsequent to providing the above information, subjects were provided with three IPCC climate policy scenarios and their anticipated consequences as presented below in Figure 3.2. The purpose of this screen was two-fold. First, we wanted to make respondents aware of current climate projections and relative policy options ranging from "Business as Usual" to "Aggressive Emissions Reductions." To a certain extent, this information also served to induce an element of moral outrage for those concerned about climate change.

In Part III, respondents were provided with an estimate of the carbon generated from their use of utilities and transportation and, after accounting for offset purchases, their estimated carbon footprint ("the total amount of climate changing greenhouse gas emissions caused directly and indirectly by your household") in tons of carbon per year. Carbon footprints were calculated using two algorithms. If participants knew their electricity and heating expenditures, information about average electricity and fuel prices in each state were used to determine annual consumption of electricity and fuel. (If participants knew their fuel expenditures but not their fuel source for heating, a weighted average of all fuel sources for the state was used.) Annual consumption of electricity was then converted into CO_2 emissions using the average CO_2 intensity for each state. Fuel consumption was converted into CO_2 emissions using information about CO2 intensity for each fuel type. If participants did not know their electricity and heating expenditures, we gathered information about their housing structure and compared it to information about average energy consumption for houses of similar age, type and size in their state, which was then used to calculate CO2 emissions as above. Information about fuel prices, generation mix and average household energy consumption was obtained from the Energy Information Administration.

Climate Options

The IPCC has presented several options for reducing climate change, each with different final levels of carbon and impacts on the global climate:

	Business as Usual	Small Emissions Reductions	Aggressive Emissions Reductions
Mean Percent change in Carbon Emissions from 2000 to 2050	115% Increase	55% Increase	70% Decrease
Global Average Temperatures Increases	8.8-11 degrees (4.9-6.1 degrees Celsius)	7.2-8.8 degrees Fahrenheit (4-4.9 degrees Celsius)	3.6-4.3 degrees Fahrenheit (2-2.4 degrees Celsius)
Sea Level Increases	12-24 inches (0.3 - 0.6 meters) Millions at risk of coastal flooding	10-24 inches (0.26 - 0.6 meters) Millions at risk of coastal flooding.	Less than 17 inches (0.45 meters)
Extinction Risk	More than 40% of species face some risk	More than 40% of species face some risk	30% of species face some risk
Crops and Famine	Crop productivity is expected to decrease. Global food production is expected to decrease, causing an increased risk of famine.	Crop productivity is expected to decrease. Global food production is expected to decrease, causing an increased risk of famine.	Crop productivity may increase in some regions and decrease in others. Increased risk of famine in some areas.
Other effects	Increase in intensity and frequency of heat waves. Increased range for tropical diseases. Together, these will cause death and sickness, placing a substantial burden on health services.	Increase in intensity and frequency of heat waves. Increased range for tropical diseases. Together, these will cause death and sickness, placing a substantial burden on health services.	Increase in intensity and frequency of heat waves.

FIGURE 3.2: Information about Climate Change Presented in On-Line Survey

Information about participants' cars and miles driven was directly computed based on combined city/highway fuel economy information from the EPA for every make, model and year of car from 1983 to 2009. For air travel, short flights were assumed to be 100 miles each way, long flights 750 miles, and international flights 4,250 miles. Carbon offsets reduced the carbon footprint by 168 pounds for every dollar spent, equivalent to prevailing rates at popular commercial carbon offset retailers.

Median estimated carbon emissions for the sample were 17.9 tons per household per year. For subjects in the control group, no other information was provided.[16] Individuals in the treatment groups were informed that "Others like you who took this survey in the past had a carbon footprint of xx tons per year" and whether their contribution was MORE or LESS than this value. The "xx" value was randomly assigned to be high (26 tons) or low (11 tons). For example, a subject with an estimated carbon footprint of 18 tons and was assigned to the "See Low" group would be told that "Others like you who took this survey in the past had a carbon footprint of 11 tons per year" and that "Your contribution to global warming is MORE than this average." Similarly, a like individual who was assigned to the "See High" treatment was "Others like you who took this survey in the past had a carbon footprint of 26 tons per year" and that "Your contribution to global warming is LESS than this average." 26 tons and 11 tons were selected because they were the average footprint from various pilot samples, that happened to be near the 25th and 75th percentile of the

[16] In pilot experiments, we also compared the results of a control group where no information about carbon footprint was given to the current control group where the carbon footprint was given without peer comparison and found no significant difference in behavior.

total sample. This ensures that on average about half of all of those treated were informed that they were relatively more culpable than others, while half received information that they were relatively less culpable. As will be discussed below, the difference between the subject's carbon footprint and the value associated with the reference individual provided a measure of relative culpability.

Given this information contingent values (CV) were elicited using a modification of a green electricity payment card used in Champ and Bishop (2001, 2006) in which individuals were given opportunities to buy blocks of energy measured in kilowatt hours. As shown in Figure 3.3 each block had a corresponding monthly and annual cost and estimated annual tons of CO2 averted based on information available from the Energy Information Administration.

Green Energy

Suppose your electric utility were to offer you renewable energy appropriate to your area. For example, wind, solar, geothermal, or tidal power could all be offered, depending on your geographic location. Choose the option you would like to purchase from the table below. (Information from the Energy Information Administration of the Department of Energy.)

	Size of Block	Extra Cost per Month	Extra Cost per Year	Tons of CO2 Averted per Year
O	0 kilowatt hours	$0.00	$0.00	0 tons
O	50 kilowatt hours	$2.80	$33.60	0.405 tons
O	100 kilowatt hours	$5.60	$67.20	0.81 tons
O	200 kilowatt hours	$11.20	$134.40	1.62 tons
O	300 kilowatt hours	$16.80	$201.60	2.43 tons
O	400 kilowatt hours	$22.40	$268.80	3.24 tons
O	500 kilowatt hours	$28.00	$336.00	4.05 tons
O	600 kilowatt hours	$33.60	$403.20	4.86 tons

Submit

FIGURE 3.3: Elicitation Question for Contingent Valuation in On-Line Survey

In Part IV, debriefing and demographic questions were asked, along with ten questions designed to measure environmental concern drawn from the New Environmental Paradigm (NEP) scale (Dunlap and Van Liere, 1978; Dunlap et al. 2000.) This scale is widely used in the psychology and sociology literature to characterize an individual’s environmental concern based on the extent to which they agree or disagree with various statements of environmental concern:

> “limits to growth, anthropocentrism, the fragility of the balance of nature, rejection of the idea that humans are exempt from the constraints of nature, and the possibility of an eco-crisis or ecological catastrophe. The response categories range between 1 and 5 so that high scores correspond to a stronger pro-environmental attitude than low scores (with the ordering reversed for the statements that reject the NEP-paradigm)” (Ek and Söderholm, 2008, p. 175)

Past studies of willingness to pay for green electricity have found the aggregated values across a series of NEP questions to be a significant, exogenous explanatory variable (Kotchen and Moore, 2007; Ek and Söderholm, 2008). We also asked subjects their political party identification, and political orientation on a Likert scale that ranged from “Very Liberal” to “Very Conservative”.

Twelve observations in our data set were identified as outliers and excluded from analysis: ten of these observations were excluded because at least one component of their carbon footprint was much greater than the rest of the sample, often an order of magnitude more. These observations were unrealistically high values, appearing to be incorrectly entered responses as to miles driven, airline flights, carbon offsets purchased, or housing information. The other two observations are repeated surveys. Removing these twelve observations halves the mean of the reported carbon footprint and reduces the standard deviation by an order of magnitude.

Lab Experiment:

We endeavored to develop a parallel experimental economics laboratory in which subjects purchase “private commodities” (analogous to electricity) that generate a negative public externality (analogous to pollution) for a group in which they are a member. The subjects are subsequently given an opportunity to contribute to a fund that would reduce the negative harm created by the externality, akin, we believe to the opportunity to purchase green electricity.

Subjects (n=240) were recruited from a variety of undergraduate business and economics courses at Cornell University. Pen and paper experimental sessions were conducted in the Laboratory for Experimental Economics and Decision Research in cohorts ranging in size from 10 to 20. A session lasted approximately 45 minutes and average earnings were $14.41.

Subjects were randomly assigned into groups of five anonymous participants including themselves. Adapting Plott's (1983) seminal externality experiments, each individual was given a balance of $9 at the beginning of each of five rounds and a per-unit value (demand) function for a commodity that could be purchased at a cost of $1 (experimental dollars were converted to real dollars at a rate of $15 experimental = $1 real.) Subjects in each group were randomly assigned into high, low and medium demands and the choices offered to individuals were presented (see Appendix for full experimental instructions).

In addition to private return for each commodity unit purchased, subjects were informed that each unit purchased would impose a negative externality on the entire group,

> *Your group also shares a GROUP FUND. This group fund began with 300 experimental dollars, and at the end of the experiment, any dollars in this group fund will be divided equally between all members of the group. Your actions and the actions of other people in your group in Round 1 may have reduced the total amount of dollars remaining in the group fund.*

> *In Round [1-5], every unit of the commodity that you purchase decreases the number of experimental dollars in the group fund by 1.25. (Because there are five people in your group, every unit of the commodity that you purchase reduces the amount in the group fund by 0.25 dollars per person. Likewise, every unit of the commodity purchased by everyone else in the group reduces the amount in the group fund by 1.25 dollars and therefore costs everyone else 0.25 dollars.)*

Hence, the optimal private decision would be to purchase only those commodities with a value of $1.25 or higher. Examples were worked through with the entire session on a whiteboard at the front of the lab, and after each decision, subjects were asked to calculate and report their own private returns and the impacts of their private decisions on other members of the group. Subjects were asked to sum their commodity purchases over the first five rounds and write this number down on a "passing sheet" which was submitted to the experimental moderator. The experimental moderator passed these sheets back to other subjects, who were then asked to record their own total purchases and the amount of total purchases that they saw on the sheet that was passed to them. Those in the high culpability treatment received the sheet of someone else with low demand, those in the medium culpability treatment received the sheet of someone with medium demand, those in the low culpability treatment received the sheet of someone with high demand, and those in the control received their own sheet back again. As in the CV experiment, we dropped 14 out of 240 outliers from analysis on the assumption that they were not paying attention carefully to the rules of the game. These were the subjects that chose to consume more than what was even privately optimal (i.e. they consumed at levels where the private cost exceeded the private benefit).

IV. Analysis and Results

Contingent Valuation Experiment

Our analyses of the contingent valuation and laboratory experiments breaks the sample into treatment and control groups. In the contingent valuation "Treatment" group, subjects were informed about the carbon footprints of "Others like [them] who took this survey in the past", with others like them corresponding to the "See Low" (n=111) and "See High" (n=84) information described previously. Similarly, the "Treatment" group in the Lab Experiment is organized by whether subjects were passed information from a subject with a "High" (n=63), "Medium" (n=29) or "Low" (n=62) induced demand. No such relative information was provided to the "Control" groups in the contingent valuation (n= 79) and lab (n =64) experiments.

Averages for the control and treatment groups are provided in Table 3.1 for the contingent valuation experiments. In the contingent valuation experiment, the dependent values reported are annual willingness to pay for green electricity. As these data are not conditioned on other possible covariates, some caution should be taken in interpreting the treatment effects. However, it is particularly notable that in both cases, providing information appears to either not affect average contributions or has a negative effect relative to the control group. The high culpability (11 ton) inducement yielded the same average willingness to pay ($143.40) as the control ($143.33). The low culpability inducement led people to contribute less ($107.68). This would suggest that providing social norms tends to lower willingness to pay values. The average willingness to pay of the full treatment group was ($128.20). If these results generalize, then contingent valuation studies that fail to provide information about peers would provide higher values than studies that provide such information, regardless of whether the individual is higher or lower than the norm. Such a result corresponds to the "broken windows" effect that observing others violate one social norm makes subjects more likely to violate other social norms. (Keizer et al. (2008)

TABLE 3.1: Summary Statistics for Contingent Valuation Experiment

	By Treatment Group			Treated: By Culpability	
	Control	Saw 11 Tons	Saw 26 Tons	Saw Low Footprint	Saw High Footprint
WTP (Average of lower bound of interval)	143.33	143.40	107.68	152.26	96.40
	(15.41)	(12.30)	(12.98)	(12.87)	(11.46)
CO2 Total	23.30	20.84	25.91	32.01	11.08
	(2.35)	(1.85)	(2.64)	(2.34)	(0.67)
Relative Culpability		9.84	-0.09	16.96	-9.38
		(1.85)	(2.64)	(2.18)	(0.72)
NEP	34.01	35.25	34.65	34.37	35.82
	(0.81)	(0.67)	(0.82)	(0.71)	(0.75)
Politics	0.75	0.75	0.66	0.73	0.69
	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
Children	0.58	0.50	0.53	0.63	0.36
	(0.06)	(0.05)	(0.06)	(0.05)	(0.05)
Gender	0.57	0.49	0.49	0.47	0.52
	(0.06)	(0.05)	(0.06)	(0.05)	(0.05)
Age	37.61	37.50	40.39	36.86	41.20
	(1.17)	(1.19)	(1.40)	(1.10)	(1.50)
Income	5.04	4.65	4.30	4.94	3.93
	(0.23)	(0.17)	(0.21)	(0.17)	(0.20)
Education	0.53	0.53	0.46	0.55	0.43
	(0.06)	(0.05)	(0.06)	(0.05)	(0.05)
Democrat	0.41	0.46	0.34	0.41	0.40
	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
N=	79	112	83	111	84

Summary statistics for Not outliers, with no missing observations
Standard Errors in parentheses
CO2 Total: Total CO2 Footprint
Culpability: Total CO2 Footprint – (11 or 26 tons, depending on treatment)
NEP: Aggregate NEP value

Politics: Binary for liberal/conservative (1 if liberal)
Children: Binary for children in household
Gender: Binary for gender (1 if female)
Age: Age of respondent
Income: Household income in levels (0: <$10K, 1: $10K-$15K, 2: $15K-$25K, 3: $25K-$35K, 4: $35K-$50K, 5: $50K-$75K, 6: $75K-$100K, 7: $100K-$150K, 8: $150K-$200K, 9: >$200K
Education: Binary for education (1 if at least college education)
Democrat: Binary for party affiliation (1 if democrat)

Columns (4) and (5) show the summary statistics divided by those who saw peer information lower ("saw low") or higher ("saw high") than themselves. While the willingness to pay in these columns cannot be cleanly interpreted because membership in saw high or saw low is endogenous and depends on own carbon footprint, dividing the dataset in this way will be useful when we turn to regression analysis to understand the asymmetry in behavior. However, we address the endogeneity directly in the lab experiment.

Econometric modeling reveals more about the structure of how subjects responded to the peer information. In modeling the responses to the contingent valuation experiment, the dependent variable we use is "extra cost per year." Given the discrete, ordered nature of the payment card response options, we extend Cameron's expenditure difference model (1988) to the interval modeling format developed in Cameron and Huppert (1989), wherein circling a particular threshold value provides the lower bound of a willingness to pay (WTP) interval bounded from above by the next cost point. Assuming a logistically distributed WTP function, and letting E(WTP) = γZ and var(WTP) = σ^2 yields the following log likelihood function:

$$Ln(L) = \sum_{i=1}^{n} \ln\left[F\left({(\gamma Z_i - t_{iU})}/{\theta}\right) - F\left({(\gamma Z_i - t_{iL})}/{\theta}\right)\right],$$

where F(.) indicates the logistic distribution, Z is a vector of covariates, t_{iU} is the upper bound of the interval selected, t_{iL} is the lower bound, and the scale parameter $\theta = \sigma\sqrt{3}/\pi$.[17] Throughout, robust standard errors are reported, based on the Huber-White heteroskedasticity-consistent-covariance-matrix estimator.

For the treatment group, we constructed a relative culpability variable measuring the difference between the subject's carbon and the "other" carbon footprint he/she was shown.

Culpability = Own footprint – Observed footprint of others

In specifications where we include the control group which had no information about their peers, we set culpability to zero on the assumption that people assume their footprint is about the same as others. However, since it is reasonable to assume that the effect of culpability differs depending on whether peer information was made available, we focus on the regression specifications that drop subjects in the control condition. In the regressions reported in Table 3.2, we also included controls for the subject's own carbon footprint (CO2 Footprint), the NEP scale response summed over the 10 Likert scale NEP questions (NEP)[18], and a self-reported political scale (Political Scale) variable extending from 0 (very liberal) to 6 (very conservative), which has been recoded into a binary variable for liberal political leaning at the median of the sample. These latter two variables comport with the environmental and political orientation variables in the Costa and Kahn study (2010). In addition, standard

[17] These regressions were also all done with OLS and Tobit (because of non-negativity constraints), as well as Huber-White (heteroscedasticity-consistent covariance matrix estimator) standard errors and (for the lab experiment) corrections for cluster-level standard errors. All these alternate models produced essentially the same results.
[18] The Cronbach alpha value for the subjects for the NEP questions was 0.7785, generally consistent with the literature, and indicating that the NEP is a coherent metric.

demographic and socio-economic variables of the type typically included in contingent valuation research (age, gender, children in household, income and education) are added as covariates.

TABLE 3.2: MLE Results for Contingent Valuation Experiment

	Control	Treated			
		Continuous Culpability		Conditional Culpability	
		Full Model	Short Model	Full Model	Short Model
Constant	-127.41	-35.04	-36.32	-32.97	-32.25
	(113.61)	(56.77)	(48.63)	(56.82)	(49.15)
Relative Culpability>0				3.60**	3.36**
				(1.52)	(1.52)
Relative Culpability<0				2.64*	2.34
				(1.50)	(1.50)
Relative Culpability		3.11***	2.84**		
		(1.17)	(1.17)		
CO_2 Footprint	0.58	-0.89	-0.63	-1.25	-0.99
	(0.88)	(1.22)	(1.23)	(1.41)	(1.40)
NEP	7.41***	4.63***	5.16***	4.57***	5.08***
	(2.49)	(1.28)	(1.20)	(1.28)	(1.21)
Politics	5.98	9.93		9.84	
	(38.02)	(20.01)		(19.97)	
Children	9.25	26.07		27.50	
	(35.85)	(18.74)		(18.95)	
Gender	-23.46	-22.73		-22.20	
	(36.05)	(17.76)		(17.77)	
Age	0.42	1.12		1.12	
	(1.75)	(0.72)		(0.72)	
Income	-2.82	-8.51		-8.24	
	(8.56)	(5.56)		(5.58)	
Education	48.17	15.06		14.74	
	(35.55)	(18.48)		(18.47)	
Theta	80.46***	67.94***	69.38***	67.83***	69.26***
	(8.30)	(4.31)	(4.39)	(4.31)	(4.39)
Observations	79	195	195	195	195
Log Likelihood	-176.44	-424.85	-428.41	-424.72	-428.27

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

All samples exclude outliers and observations with any missing samples

Table 3.2 reports estimation results for Full Models with all the aforementioned covariates and Short Models with only a subset of the variables. The vector of covariates was organized into three sub-vectors: 1) Estimation Variables (Constant, Theta); 2) Culpability Measures (Relative Culpability > (<) 0; Relative Culpability, CO2 Total); and 3) Demographic Variables (NEP, Politics, Children, Age, Income, Education). For both the latter two groups the estimation strategy followed the pretest estimation procedure presented in Goldberger (1991) wherein Likelihood Ratio Tests were used to test the zero-null-vector hypothesis for the entire group (which was rejected in all cases). This was followed by a stepwise procedure in which the most insignificant coefficients were sequentially dropped. Coefficients were retained in the short model if their corresponding p values were less than the cutoff value of 0.15. Further, CO2 Total was kept as a control variable in all estimations.

The econometric analysis reveals that though on average, those who received peer information were willing to contribute less than those who did not, people are indeed positively and significantly influenced by relative culpability—those who were induced to feel relatively more culpable were willing to pay more than those who were induced to feel relatively less culpable. Specifically, for each ton of CO2 a person is led to believe that she polluted more than others, her willingness to pay increases by \$2.84 to \$3.11. For context, the mean culpability score for someone who saw a lower footprint was 16.96 tons, and the mean WTP for the control group was \$143.33. In addition to the estimation variables, culpability, and CO2 Total, Only the NEP covariate was retained in the Short Model.

To better reconcile the regression results with the aggregate effects, we interact binary variables for those with positive culpability scores (those who are induced to feel more culpable than others) and those with negative culpability scores (those who are induced to feel less culpable than others) with the relative culpability measure. This is referred to as "Conditional Culpability" in Table 2. Columns (4) and (5) present the results and find evidence that the impact of peer information is asymmetric. Those who are more culpable than those they observed significantly increase their WTP by \$3.36-\$3.60 for each ton of additional culpability. There is no significant effect of relative culpability for those who are less culpable than those they observed ($p=0.326$ in a z-test). Note that since we control for each individual's own CO2 footprint, the coefficient on culpability is identified off the exogenously assigned treatment group. There remains the concern that in this asymmetry, we are merely capturing the difference between those with high footprint and low footprint in a way that is not controlled for by the inclusion of the footprint variable (perhaps due to a non-linear relationship). To address this concern, we rely on the results from the lab experiment where footprint is exogenously assigned.

Lab Experiment

In order to better isolate the effect of culpability we rely on the results of a context-free lab experiment in which an individual's impacts on the public good is an outcome of an induced demand for the private good. Since culpability depends only on own consumption levels and the observed consumption levels of others, the lab experiment allows a degree of exogenous control over both components.

Table 3.3 presents the summary statistics for the lab experiment. Note once again, that even though positive culpability was induced for two of the three treatment conditions, as before, all conditions yielded less (or at most equal) altruistic behavior than the control (3.41 tokens). On average, it appears that information on culpability leads to less altruistic behavior in both CV and experimental laboratory settings.

TABLE 3.3: Summary Statistics for Laboratory Experiment

	Control	Entire Sample By Induced Demand			Treated By Culpability		
		Small	Medium	Large	Saw Smaller	Saw Larger	Saw Same
Round 6 Purchases	3.31	2.38	2.79	3.42	2.81	2.78	0.83^
	(0.45)	(0.37)	(0.56)	(0.38)	(0.40)	(0.43)	(0.48)
Relative Culpability	n.a.	-5.78	3.55	11.23	-3.60	16.59	0.83
		(1.04)	(1.28)	(1.16)	(1.65)	(1.09)	(3.31)
Total Purchases	18.27	12.86	18.97	23.51	13.10	25.49	22.67
	(1.13)	(0.36)	(0.98)	(1.11)	(0.56)	(1.01)	(3.95)
NEP	24.23	22.70	25.67	24.26	22.63	24.94	25.33
	(0.72)	(0.60)	(1.10)	(0.64)	(0.60)	(0.89)	(2.43)
Liberal	0.58	0.68	0.48	0.54	0.63	0.53	0.67
	(0.06)	(0.06)	(0.09)	(0.06)	(0.06)	(0.07)	(0.21)
Democrat	0.45	0.54	0.42	0.44	0.55	0.41	0.50
	(0.06)	(0.06)	(0.09)	(0.06)	(0.06)	(0.07)	(0.21)
Observations	64	69	33	81	62	51	6

All samples are excluding “greater than ideal”: people whose purchases exceeded the private optimum and likely misunderstood the experiment. All samples also exclude any observations with any missing responses.
Standard errors in parentheses.
^: Value is less than control at $p<0.05$

Since each unit of a subject’s consumption choice generates negative externalities on others in the experimental session, we use their consumption choice as the analogue for “carbon footprint.” Also, in order to ensure the exogeneity of the culpability variable, we use the expected target footprint he would have been induced to select if he were a completely self-interested rationally maximized individual given the treatment condition he was in (high demand, medium demand, low demand) instead of using the subject's actual own "footprint" minus footprint of others,. This measure is highly correlated with actual culpability (ρ = 0.7799), but ensures that the culpability score is exogenous and not correlated with subject characteristics like altruism, as is possibly the case in the CV experiment.

Lab Culpability = Induced target footprint – Observed footprint of others

Table 3.4 presents the maximum likelihood estimates using the same econometric model and estimation strategy as the one used for the CV experiment, with similar asymmetric patterns emerging. Relative culpability is not significant in the full sample, and indeed the only significant coefficient is that of the politics covariate. When the estimation separates those who were either above or below the norms shown, those with relatively high induced relative culpability provide significantly more to the public good in the short, but not the full model. There is an insignificant effect for those with less relative culpability. Note that we used a maximum likelihood model here to be consistent with the CV specification, but we also tested OLS, Tobit, and an IV specification where we used the exogenously assigned treatment group as an instrument for culpability in a reviewer's appendix. We also repeated those specifications, clustering by experimental group. These alternate specifications yielded largely similar results.

TABLE 3.4: MLE Results for Laboratory Experiment					
	Control	Treated			
		Continuous Culpability		Conditional Culpability	
		Full Model	Short Model	Full Model	Short Model
Constant	0.51	2.88*	1.71	2.42	2.00*
	(3.17)	(1.61)	(1.23)	(1.63)	(1.16)
Relative Culpability>0				0.06*	0.07*
				(0.04)	(0.04)
Relative Culpability<0				-0.03	-0.05
				(0.05)	(0.05)
Relative Culpability		0.02	0.02		
		(0.02)	(0.02)		
Total Purchases	-0.01	-0.01	-0.02	-0.01	-0.03
	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
NEP	0.14	-0.05		-0.04	
	(0.10)	(0.05)		(0.05)	
Politics	0.71	0.87	0.93*	0.74	
	(1.03)	(0.56)	(0.56)	(0.56)	
Experimental Dummies?	Yes	Yes	Yes	Yes	Yes
Theta	1.94***	1.55***	1.56***	1.54***	1.56***
	(0.20)	(0.12)	(0.12)	(0.12)	(0.12)
Observations	64	119	119	119	119
Log Likelihood	-168.79	-290.11	-290.74	-289.27	-290.70

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
All samples are excluding "greater than ideal": people whose purchases exceeded the private optimum and likely misunderstood the experiment. All samples also exclude any observations with any missing responses.

Note while the culpability variable is insignificant for the full sample, we again see the asymmetric effect when one sees higher others compared to seeing lower others in the short model.

V. Heterogeneity in Responsiveness to Norms

Costa and Kahn (2010) noted the heterogeneous effect of the peer information experiment on Democrats vs Republicans. We confirm their findings by dividing the data into self-identified "Democrats" (a relatively liberal party in the United States) and all others (Non-DEM). We extend their work by also considering heterogeneity in other dimensions, including liberal versus conservative, number of children, gender, age, income, education, and NEP score, available for the relatively diverse contingent valuation study. For each of these socio-economic dimensions, we partitioned our sample along the median, and ran the same estimation models as above for each partition. Summary statistics and correlation tables are found in the reviewer's appendix—note that although these demographic characteristics are correlated, the correlations are quite low.

We first note that our results are consistent with Costa and Kahn (2010). As shown in column (1) of Table 3.5, the coefficient on culpability for Democrats was positive and significant, indicating that such individuals are responsive to social norm nudges. Indeed, in the regression this parameter dominates in the sense that the coefficients for the other explanatory variables are not significant. As shown in Column (3), however, neither the coefficient for Culpability nor for the CO2 Footprint are significant: non-democrats are not affected by our culpability inducement. Yet, coefficients for NEP and Political Scale are significant and consistent with expectations in the Non-Dem regressions.

It is evident that this heterogeneity in response patterns extends to other dimensions. We find that culpability is effective for liberals but not non-liberals; for those with children but not for those without children; for men but not for women; for those older than 36.5 but not those younger; for those above approximately $50,000 for income but not for those below; for those with a college degree but not for those without; for those who are more environmental conscious (NEP score > 34.5)..

A possible explanation for the patterns in Tables 3.5 – 3.7 is that peer information nudges work on those already inclined to give, but do not work and may even backfire when preaching to those less inclined. It is also possible that in the specific context of climate change, those who question the premise of whether climate change is happening may be unresponsive. Also, the fact that the effect of culpability on those with high versus low carbon footprints allows us to rule out the hypothesis that the heterogeneity in other dimensions like income or age, only because those dimensions are correlated with carbon footprint.

We should be careful to note that this heterogeneity analysis should be seen as exploratory and mostly provided to be suggestive for future work. However, the fact that such heterogeneity exists appears quite robust. Awareness of this heterogeneity is important for increasing the precision of estimates of the effect of peer information interventions, as well as for increasing the cost effectiveness of future norm based interventions.

VI. Conclusions

Using a contingent valuation framed field experiment coupled with a conventional lab experiment to examine how peer information that induces culpability differs from peer information interventions based on conformity. We demonstrate that there is important heterogeneity in how altruism responds to such peer information.

We find similar patterns of heterogeneity for both the online contingent valuation experiment and the context free lab experiment using a convenience sample. We find the culpability effect is larger when the information makes the subject feel good about themselves, then when the information makes them feel guilty. This result has potentially important implications for public policy. Strategies that induce culpability affect primarily individuals who are more inclined to reduce energy consumption in first place. As a consequence, they are likely to be highly cost-ineffective and should not be seen as substitute for more traditional policies that are likely to alter the behavior or the entire population. Prospect Theory (Kahneman and Tversky 1979) may also explain this asymmetry in response. In our results, people whose footprints exceed the reference amount would find themselves in the loss domain, and weight such a loss more heavily than the gain of being below the reference amount. However, we leave a fuller development of such theoretical implications to future research.

TABLE 3.5: Summary Statistics Split by Demographic Subgroup for Contingent Valuation Experiment

	Liberal	Not Liberal	Children	No children	Male	Female	Age>36.5	Age<36.5
WTP, average of Lower Bound of interval	137.3	105.6	142.46	113.18	137.12	119	138.6	118.11
	(11.09)	(14.94)	(12.94)	(12.47)	(12.38)	(13.18)	(13.73)	(11.79)
Relative Culpability	6.13	4.34	10.86	0.09	9.53	1.58	0.09	10.97
	(1.91)	(2.81)	(2.18)	(2.17)	(2.61)	(1.68)	(1.37)	(2.72)
Total CO2	23.06	22.84	28.46	17.25	26.89	18.98	17.96	27.88
	(1.87)	(2.82)	(2.12)	(2.13)	(2.60)	(1.57)	(1.26)	(2.72)
NEP	36.43	31.43	34.66	35.35	34.1	35.92	36.22	33.81
	(0.61)	(0.81)	(0.70)	(0.76)	(0.69)	(0.76)	(0.77)	(0.68)
Politics	1	0	0.73	0.69	0.69	0.74	0.65	0.78
	(0.00)	(0.00)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)
Children	0.53	0.48	1	0	0.49	0.53	0.43	0.6
	(0.04)	(0.07)	(0.00)	(0.00)	(0.05)	(0.05)	(0.05)	(0.05)
Married	0.58	0.77	0.8	0.46	0.66	0.61	0.72	0.56
	(0.04)	(0.06)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Gender	0.51	0.45	0.51	0.47	0	1	0.51	0.47
	(0.04)	(0.07)	(0.05)	(0.05)	(0.00)	(0.00)	(0.05)	(0.05)
Income	4.56	4.36	5.07	3.91	4.62	4.39	4.35	4.65
	(0.16)	(0.24)	(0.17)	(0.19)	(0.21)	(0.17)	(0.18)	(0.20)
Age	37.22	42.46	36.84	40.72	38.38	39.08	49.67	28.12
	(1.01)	(1.86)	(0.99)	(1.53)	(1.31)	(1.26)	(0.83)	(0.50)
Education	0.52	0.45	0.54	0.45	0.59	0.41	0.43	0.57
	(0.04)	(0.07)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Democrat	0.53	0.13	0.42	0.4	0.31	0.51	0.42	0.4
	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Observations	139	56	100	95	99	96	96	99

Table 3.5 (Continued)

	Income>4.7	Income<4.7	At least college	No college	Dem	Not Dem
WTP Lower Bound	139.85	112.8	135.79	120.69	139.44	120.38
	(12.03)	(13.58)	(12.25)	(13.29)	(14.01)	(11.82)
Relative Culpability	10.46	-0.8	9.71	1.56	4.9	6.11
	(2.27)	(1.92)	(2.60)	(1.73)	(2.38)	(2.12)
Total CO2	27.55	16.99	26.59	19.45	21.15	24.29
	(2.26)	(1.83)	(2.64)	(1.58)	(2.41)	(2.03)
NEP	34.3	35.92	34.67	35.32	36.41	34.01
	(0.62)	(0.87)	(0.68)	(0.78)	(0.71)	(0.71)
Politics	0.73	0.69	0.74	0.68	0.91	0.57
	(0.04)	(0.05)	(0.04)	(0.05)	(0.03)	(0.05)
Children	0.62	0.37	0.56	0.47	0.53	0.5
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)
Married	0.74	0.5	0.68	0.59	0.6	0.66
	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)	(0.04)
Gender	0.43	0.57	0.4	0.58	0.61	0.41
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Income	5.78	2.81	5.07	3.94	4.74	4.34
	(0.09)	(0.15)	(0.19)	(0.17)	(0.18)	(0.19)
Age	38.16	39.48	37.38	40.06	38.61	38.81
	(1.12)	(1.51)	(1.18)	(1.37)	(1.43)	(1.19)
Education	0.6	0.36	1	0	0.58	0.44
	(0.05)	(0.05)	(0.00)	(0.00)	(0.06)	(0.05)
Democrat	0.45	0.36	0.47	0.35	1	0
	(0.05)	(0.05)	(0.05)	(0.05)	(0.00)	(0.00)
Observations	111	84	97	98	80	115

TABLE 3.6: MLE Results for Democrat/Non-Democrat Split: Contingent Valuation Experiment

	Democrat		Not Democrat	
	Full Model	Short Model	Full Model	Short Model
Constant	13.83	184.54***	-34.96	2.35
	(112.9)	(37.41)	(66.09)	(61.66)
Relative Culpability	5.577**	4.20**	1.942	2.00
	(2.277)	(2.02)	(1.386)	(1.40)
CO2 Footprint	-3.200	-2.28	0.334	0.42
	(2.162)	(2.04)	(1.479)	(1.49)
NEP	3.509		4.957***	5.42***
	(2.381)		(1.467)	(1.37)
Politics	-54.25		14.35	
	(53.74)		(22.38)	
Children	26.38		31.28	
	(30.26)		(24.19)	
Gender	24.78		-42.37*	-44.93**
	(30.86)		(22.86)	(21.55)
Age	5.145		-16.00***	
	(10.22)		(6.107)	
Income	1.305		0.951	-12.19**
	(1.377)		(0.838)	(5.87)
College	-3.200		24.09	
	(2.162)		(23.50)	
Theta	69.17***	73.40***	63.09***	64.07***
	(6.824)	(7.14)	(5.261)	(5.35)
Observations	80	80	115	115
Log Likelihood	-174.5	-178.38	-244.1	-246.22

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 3.7: MLE Results for Demographic Subgroups for Contingent Valuation Experiment (Full regression)

Subgroup	Culpability Coefficient
Liberal	3.33***
Not Liberal	2.58
Children	4.54***
No Children	1.88
Male	3.10**
Female	2.89
Age>36.5	5.14***
Age<36.5	1.10
Income>4.7	5.47***
Income<4.7	0.16
At least College	4.21***
Less than College	1.98
NEP>34.5	4.63**
NEP<34.5	1.55
Democrat	5.58**
Not Democrat	1.94

*** p<0.01, ** p<0.05, * p<0.1

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APPENDIX

Appendix Table 3.1 Provides results for the OLS, Tobit, and IV specifications for the Lab Experiment results. The Tobit specification deals with the non-negativity constraint on the amount of public goods we allow each subject to provide. The IV uses the induced target culpability based on the exogenously assigned treatment group as an instrument for actual culpability, to ensure that the culpability variable is exogenous. In columns 1 and 2 of Table 9, the effects of culpability (the difference between a subject's own purchases in rounds 1 through 5 and the purchases of the subject whose information he or she saw) has no significant impact on purchases of the public good in round 6, even when we restrict our sample to just those subjects who received information not their own. However, when we split our sample between in those who self-identify as Democrats versus those who do not, we see a significant, positive impact on culpability and footprint on contribution, compared with those who do not self-identify as Democrats. (Compare columns three and four.) Columns five and six repeat this analysis of sub-sections of the data with a Tobit model, to check for biased estimates of coefficients due to censoring of allowed values of the contributions to the public good below zero. Finally, instrumental variables are used to control for the confounding effects of people who voluntarily purchase less than the privately optimal amount of the goods in rounds 1-5 on contribution to the public good. Such a subject would have already made a sacrifice by forgoing possible earnings in the first five rounds in order to cause less harm to the group, and thus their culpability is affected. By using a dummy for the type of subject (small or large) they received from as an instrument for culpability, we can control for this effect, and confirm the positive correlation between culpability and contribution to the public good for Democrats.

Appendix Tables 3.2 and 3.3 provides summary statistics and a correlation matrix for the demographic splits.

APPENDIX TABLE 3.1: Effect of Culpability on Contribution to a Public Good

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS				Tobit		IV	
	Full	Treated	Dem	Not Dem	Dem	Not Dem	Dem	Not Dem
Relative Culpability	-0.0022	-0.00285	0.166***	-0.0352	0.240***	-0.0556	0.158**	0.0108
	(0.0287)	(0.0327)	(0.0521)	(0.0503)	(0.0710)	(0.0652)	(0.0705)	(0.0734)
Footprint (Total Contribution, Rounds 1-5)	0.00119	0.0106	-0.230***	0.0488	-0.366***	0.0687	-0.220**	-0.006
	(0.0368)	(0.0534)	(0.0825)	(0.0807)	(0.1140)	(0.1050)	(0.1020)	(0.0989)
NEP	0.0124	-0.0435	-0.145*	-0.0227	-0.213*	-0.0674	-0.143**	-0.022
	(0.0470)	(0.0539)	(0.0818)	(0.0748)	(0.1110)	(0.1010)	(0.0707)	(0.0642)
Politics	-0.12	-0.192	-0.674*	-0.193	-0.783	-0.25	-0.665**	-0.245
	(0.1660)	(0.2000)	(0.3680)	(0.3160)	(0.4980)	(0.4060)	(0.3160)	(0.2790)
Session Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	4.128***	5.598***	12.14***	-0.197	10.37***	3.638	8.649***	5.322
	(1.5540)	(2.0340)	(3.3500)	(3.8660)	(3.7310)	(4.3400)	(2.8380)	(3.3350)
Observations	183	119	58	61	58	61	58	61
R-squared	0.064	0.177	0.474	0.246			0.474	0.232

Standard errors in parentheses

*** p<0.01, ** p<0.05, *p<0.1

APPENDIX TABLE 3.2: Summary Statistics by Demographic Split

	Age>36.5	Age<36.5	Income>4.7	Income<4.7	At least a college degree	Less than a college degree	NEP>34.5	NEP<34.5	CO_2<17.9	CO_2>17.9
WTP	135.39	114.17	134.12	111.47	131.74	117.92	138.68	110.91	147.69	106.4
	-13.15	-11.51	-11.45	-13.49	-11.95	-12.76	-12.92	-11.69	-14.21	-10.62
Relative Culp	0.02	10.28	9.57	-1.04	9.18	1.28	2.46	7.86	19.38	-6.17
	-1.35	-2.64	-2.15	-1.92	-2.52	-1.68	-2.18	-2.12	-2.62	-0.8
Total CO_2	17.93	27.25	26.7	16.84	26.12	19.2	20.08	25.12	37.63	10.62
	-1.22	-2.63	-2.12	-1.81	-2.55	-1.51	-2.08	-2.11	-2.56	-0.41
NEP	36.3	34.02	34.61	35.92	34.89	35.4	40.94	29.47	34.58	35.6
	-0.74	-0.67	-0.6	-0.87	-0.67	-0.76	-0.44	-0.43	-0.76	-0.68
Liberal	0.64	0.79	0.73	0.68	0.74	0.68	0.8	0.62	0.73	0.7
	-0.05	-0.04	-0.04	-0.05	-0.04	-0.05	-0.04	-0.05	-0.05	-0.04
Children	0.42	0.58	0.6	0.36	0.55	0.45	0.5	0.5	0.7	0.34
	-0.05	-0.05	-0.04	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.04
Married	0.72	0.53	0.72	0.49	0.66	0.59	0.61	0.64	0.78	0.5
	-0.04	-0.05	-0.04	-0.05	-0.05	-0.05	-0.05	-0.05	-0.04	-0.05
Female Dummy	0.52	0.47	0.44	0.56	0.4	0.59	0.57	0.42	0.42	0.55
	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05
Income	4.35	4.65	5.78	2.82	5.07	3.94	4.28	4.7	5.05	4.06
	-0.18	-0.19	-0.08	-0.15	-0.19	-0.17	-0.19	-0.18	-0.2	-0.16
Age	49.81	27.89	38.12	39.76	37.01	40.54	41.2	36.43	37.36	39.95
	-0.82	-0.5	-1.11	-1.52	-1.17	-1.36	-1.32	-1.2	-1.14	-1.34
Obss	102	103	120	85	101	104	102	103	91	114
Standard errors in parentheses										

APPENDIX TABLE 3.2 (Continued)

	Democrats	Not Dem	Liberal	Not Liberal	Children	No Children	Male	Female
WTP	137.72	116.25	133.9	101.94	139.62	109.69	131.8	117.43
	-13.94	-11.2	-10.8	-14.35	-12.68	-11.91	-12	-12.72
Relative Culp	4.69	5.49	5.78	3.66	10.52	-0.23	8.79	1.45
	-2.36	-2.01	-1.84	-2.72	-2.13	-2.07	-2.52	-1.63
Total CO2	21.06	23.63	22.74	22.28	28.07	17.1	26.14	18.98
	-2.39	-1.91	-1.79	-2.7	-2.07	-2	-2.5	-1.51
NEP	36.54	34.23	36.49	31.76	34.86	35.44	34.27	36.04
	-0.71	-0.68	-0.59	-0.81	-0.69	-0.73	-0.67	-0.74
Liberal	0.91	0.58	1	0	0.73	0.7	0.68	0.74
	-0.03	-0.04	0	0	-0.04	-0.05	-0.05	-0.04
Children	0.52	0.49	0.51	0.47	1	0	0.49	0.51
	-0.06	-0.05	-0.04	-0.07	0	0	-0.05	-0.05
Married	0.59	0.65	0.57	0.76	0.8	0.45	0.63	0.61
	-0.05	-0.04	-0.04	-0.06	-0.04	-0.05	-0.05	-0.05
Female Dummy	0.62	0.41	0.51	0.44	0.5	0.48	0	1
	-0.05	-0.04	-0.04	-0.07	-0.05	-0.05	0	0
Income	4.74	4.34	4.56	4.35	5.07	3.91	4.61	4.39
	-0.17	-0.18	-0.16	-0.24	-0.17	-0.18	-0.2	-0.17
Age	38.44	39.03	37.1	43.02	36.73	40.89	38.19	39.43
	-1.42	-1.18	-1.01	-1.81	-0.98	-1.5	-1.31	-1.25
Obss	81	124	146	59	103	102	104	101
Standard errors in parentheses								

APPENDIX TABLE 3.3: Correlation Matrix

	At least a college degree	Democrat	Age	Income	Female Gender	Children	Liberal	NEP	Total CO2 Footprint	Relative Culpability
Culpability	0.074	-0.0599	-0.043	-0.03	-0.1048	0.1175	0.023	-0.001	0.9985	1
Total CO2 Footprint	0.0766	-0.0613	-0.047	-0.027	-0.1095	0.1233	0.022	-0.006	1	
NEP	-0.0482	0.1764	0.193	-0.069	0.1511	-0.097	0.288	1		
Liberal	0.0251	0.3818	-0.142	0.038	0.0122	0.0163	1			
Children	0.0894	0.0164	-0.176	0.264	0.0418	1				
Female Gender	-0.1904	0.13	0.062	-0.094	1					
Income	0.3104	0.0612	-0.074	1						
Age	-0.1321	-0.0237	1							
Democrat	0.0551	1								
At least a college degree	1									